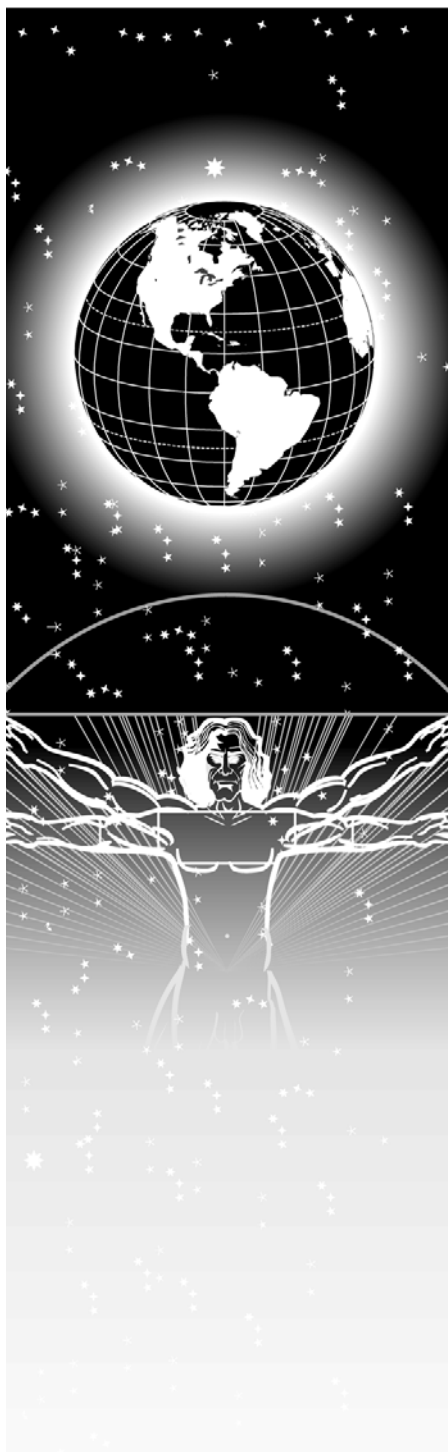




UNITED STATES AIR FORCE RESEARCH LABORATORY

COMPUTER-BASED INTELLIGENT TUTORING SYSTEMS: A COGNITIVE APPROACH TO TEAM TRAINING AND PERFORMANCE RESEARCH

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COMPUTER-BASED INTELLIGENT COMPUTER SYSTEMS: A COGNITIVE APPROACH TO TEAM TRAINING AND PERFORMANCE RESEARCH

INTRODUCTION

Advancements in computer-based technology and quantitative modeling tools represent opportunities to expand intelligent tutoring and performance engineering technology to more complex, ambiguous, and dynamic team-based settings. Computer-based systems can now portray core characteristics of complex multi-operator task environments and provide enhanced platforms for training and research in naturalistic settings. For example, military command and control (C2) scenarios have been constructed to emulate the cognitive task demands of operational C2 team members using PC-based representations of the task environment (Chiara & Stoyen, 1997; Covert et al., 2000; Hess & Elliott, 2000; Hess, MacMillan, Elliott, & Schiflett, 1999; Schiflett & Elliott, 2000) which were based on extensive accumulation of information gained from approaches such as cognitive task analysis, training requirements, and focal group information (Elliott et al., 1998, 1999, In review; Fahey, Rowe, Dunlap, & deBoom, 1997; Klinger et al., 1993; MacMillan et al., 1998).

Advanced quantitative modeling techniques and intelligent agent capabilities allow representation of other computer-based entities, such as hostile forces and fellow team members. Existing methods of knowledge elicitation must be adapted to more easily capture essential elements of a task domain—at the individual, the team, the organization, and mission levels of perspective, to generate and manipulate realistic portrayals of mission scenarios.

While advancements in technology allow more realistic and cost-effective representations of the task, we agree with Salas and his associates (Salas, Cannon-Bowers, & Kozlowski, 1997) that computer-based training has yet to be fully exploited for the advancement of the science and practice of training. Technology per se should not serve as demonstration of training improvement. Detailed replication of an environment, however complex, will not ensure psychological validity; indeed, it may not even be necessary (Berkowitz & Donnerstein, 1982; Bowers, Salas, Prince, & Brannick, 1992; Dipboye & Flanagan, 1979; Driskell & Salas, 1992). Certainly, we need to capture core characteristics of complex naturalistic environments if we mean to understand and enhance performance and skill acquisition in such situations (Brunswick, 1956; Hammond, 1993; Klein, 1997; Klein, Orasunu, Calderwood, & Zsombok, 1993; Klein & Woods, 1993; Vicente, 1997). The challenge is to identify necessary levels of fidelity to achieve instructional goals.

The application of intelligent computer-assisted tutoring technology has demonstrated great success in enhancing knowledge and skill acquisition of individuals. Computer-assisted instruction (CAI) is a mature technology, which has been successfully applied, in a wide variety of domains. The notion that carefully individualized instruction is superior to traditional linear instruction has been substantiated in numerous studies (Regian & Shute, 1992; 1998; Shute & Psotka, 1995; Woolf, 1987). Individualized instructional software autonomously modifies its behavior in response to its "model of the student's current understanding of the subject matter," based on individual performance indices (VanLehn, 1986). Further individualization of training, as demonstrated by "intelligent" computer-based systems, is theoretically consistent with models of cognitive skill acquisition (Anderson, 1983; Anderson, Corbett, Fincham, Hoffman, & Pelletier, 1992) with models that focus on motivational processes (Bandura & Cervone, 1986; Deci & Ryan, 1980; Dweck, 1986; Kanfer, 1990) and also models of training systems for complex behavior (Kozlowski, 1998; Kozlowski & Salas, 1997). It should be emphasized that the success of these advanced tutoring systems is not inherent in the technology, but rather in the principles which guide effective instruction.

The success of this approach for individuals is mitigated by the fact that individuals almost always perform in the context of teams, and instructional models have not yet addressed the consideration and measurement of teamwork performance. Instruction and feedback was at the individual level of performance, yet in operational context, the individual needs to perform in a manner that maximizes the performance of the team as a whole, and not simply his/her own performance outcomes. Instructional systems must include measures of team process and mission outcomes to enable assessment, coaching, tutoring, and/or feedback capabilities.

Team performance is not nearly as well understood as individual performance, and instructional models to optimize team performance are virtually nonexistent. No comprehensive taxonomies have been developed to provide systematic dimensions of variation across team tasks. The few postulated models of team are generally not specified sufficiently to support the generation of individualized instructional models. Our general approach is to build on critical developments in individual performance and combine these with promising approaches for modeling and optimizing team performance. First we describe principles and characteristics of individualized instruction. We then discuss application of this approach to instruction of teamwork.

Characteristics of CAI Instruction

Virtually all CAI systems are individualized in the sense that they are self-paced, and many are further individualized by virtue of branching routines that enable differential instruction. However, in branched CAI the instructional developer must explicitly encode the actions generated by all possible branches, and there must be a finite number of possible paths through these branches. As one moves further away from the CAI to the ICAI end of the continuum, one begins to see a more powerful approach to individualization. This cognitive approach is touched on by Wenger (1987) when he refers to explicit encoding of knowledge as opposed to encoding of decisions (pg. 4). In the ideal case, ICAI utilizes a diverse set of knowledge bases and inference routines to "compose instructional interactions dynamically, making decisions by reference to the knowledge with which they have been provided" (Wenger, 1987; pg. 5). Table 1 characterizes this dimension of computer-assisted instructional systems. Low, moderate, and high levels of individualization should be viewed as representing areas along a continuum of low to high individualization, rather than as discrete categories.

Table 1. Levels of Individualization in Computer-Assisted Training Systems

	Individualization of Instruction		
	<i>Low</i>	<i>Moderate</i>	<i>High</i>
Knowledge	Linear	Branched	Networked
Pedagogy	Self-paced	Adaptive	Intelligent
Package	Programmed Instruction	Computer Assisted Inst.	Intelligent CAI
Example	Pilot	WPS Tutor	StatLady

ICAI Components

In an ICAI, individualized instruction is an emergent property of several interacting components. ICAI systems usually consist of four, sometimes five, components. These are the expert module, the instructional module, the student model, the interface, and often a device simulation or other instructional environment.

The expert module is a programmed representation of expert knowledge in the target domain (that which is being taught). It is almost identical to what is commonly known as an expert system, except in this context it is often very articulate (able to generate some form of rationale for its actions) and capable of generating alternative solution paths (rather than a single “best” path). The expert module brings domain knowledge to the ICAI. It “knows” how to perform the task that it is seeking to teach and can demonstrate that knowledge.

The instructional module is a programmed representation of expert knowledge on instruction in the target domain. Its function is to adapt instructional approaches based on the current knowledge level of the student. While the expert module is typically derived from knowledge representations from an expert practitioner; the instructional module may be derived from an expert instructor in the target domain, a general training specialist, or both.

The student model constitutes a repository for information about each student who uses the system. It is a mere shell at the beginning of an initial tutoring session, whereas the expert and instructional modules are generally complete when the development of the ICAI is complete. At the beginning of an initial tutoring session the student model stores specific kinds of information about students for use by the instructional module. The student model maintains updated information about the student, such as what the student does and does not know, and any misconceptions indicated by the student. The system is “aware” of who is being taught, and can make informed decisions as to what should be instructed next and the appropriate instructional approach to be used.

The interface provides the methods by which the student interacts with the ICAI. The interface may include such output methods as computer-generated graphics and text, recorded video images, or speech synthesizers; and such input devices as a mouse, keyboard, touchscreen, joystick, or voice recognition system. One important point about the interface is that it should be as simple as possible so that learning to use the ICAI does not interfere with learning from the ICAI.

Device Simulation. Many ICAI systems (e.g., STEAMER, IMTS/Bladefold, Sherlock) use an embedded computer simulation of the electrical or mechanical device, when the goal is to understand, operate, and/or troubleshoot the device. Other ICAI systems teach a body of knowledge that is not specific to a particular device, but use simulations to provide an instructional context. For example, “Smithtown” uses a simulation of microeconomics operating in a small town, and our orbital mechanics tutor uses a simulation of orbital dynamics.

ICAI and Group Instruction

The ICAI automated instruction paradigm has been focused on instructing individually performed tasks to individuals. In fact, the ICAI approach is the contemporary epitome of “individualized” instruction. However, previous efforts have acknowledged the relevance of important social factors, such as observational learning, that may be very beneficial in learning certain kinds of tasks. These considerations have caused us to explore automated instructional systems that teach small

Table 2. Components of Intelligent Computer-Assisted Training Systems

ICAI Components	Function
Expert Module	Representation of expert knowledge, including rationale & alternatives
Instructional Module	Expert knowledge on instructional approaches in target domain
Student Model	Information regarding student patterns of performance
Interface	Information representation and distribution, Simulation of task environment

groups rather than individuals (Shebilske & Regian, 1992). Progress has been significant in the effort to automate group-based instruction for tasks that are performed by individuals. Research in our laboratory has supported the notion that computer-based training (CBT) can, in some cases, be made more effective and less costly, by focusing on group training.

Shebilske, Regian, Arthur, and Jordan (1992), examined a dyadic Active Interlocked Modeling (AIM) protocol, in which each trainee controls half of a complex task (i.e., Space Fortress), allowing each to learn the critical connections by modeling the actions and reactions of their partner. Shebilske, Jordan, Arthur and Regian (1993) expanded the dyadic protocol to include two more trainees, who rotate through task engagement and passive observation. The results revealed that four trainees could learn as well as one, with less than one-third the hands-on practice, trainer time, and resources. Similarly, Goettl and Connolly Gomez (1995) using a desktop-flight simulator task (Phoenix) found superior performance for subjects who observed compared to subjects in a no-observation control condition. It should be noted that this improvement was obtained in a task that had significant cognitive and strategic elements, but was not obtained for a task that was primarily perceptual-motor in nature. Based upon the results of these studies, Shebilske and colleagues concluded that “theories of automatization will have to be expanded to incorporate the role of observational learning” (Johnson, Regian & Shebilske, 1994, p. 6). So far results indicate that the cost-effectiveness of group-based observational learning may depend on the degree to which task demands are cognitive/perceptual as opposed to psychomotor/motor in nature. Systematic investigation should verify this interaction and identify other characteristics that would enable more accurate evaluation of this approach.

Group-based discussion is another group instructional technique, which should be further studied. We have explored discussion groups using the Space Fortress task. Prislin, Jordan, Worchel, Tschann-Semmer and Shebilske (1996) found that discussion groups resulted in improved performance, particularly for females. Male/female differences have been noted for different cognitive skills, group problem solving strategies, team effectiveness in different types of tasks, and communication style in general (Matheson, 1991; Taps & Martin, 1990). These differences should be identified to further understand the nature of these differences and design interventions to optimize team performance.

Group-based instruction can also affect the degree to which trainees will be collaborative or competitive. Collaboration and competitiveness can be induced through manipulation of features such as:

- Private versus public feedback (Nordstrom, Lorenzi, & Hall, 1991; Pritchard, Jones, Roth, Stuebing & Ekeberg, 1988; 1989)
- Performance versus mastery goals (Dweck, 1986; Kozlowski, 1996; Kozlowski et al., In press)
- Reward systems (Latham & Locke, 1991; Locke & Latham, 1990; Pritchard et al., 1988; 1989)
- Degree of interdependence (Mitchell & Silver, 1990; Saavedra, Early & Van Dyne, 1993)

Prislin et al. (1996) examined the effects of competition on skill acquisition. Competition produced beneficial effects on skill acquisition when it was introduced late in training and inhibitory effects when it was introduced early in training. This is consistent with the literature on mastery versus performance goals (Kozlowski, 1996; Dweck, 1986). The study also showed that effectiveness of individual versus dyadic training was moderated by the level of interaction anxiety of the trainees. Trainees with high anxiety demonstrated higher performance in individual conditions, while subjects low in interaction anxiety had higher performance in dyads.

These findings confirm the importance of social factors in skill acquisition and argue for a new generation of ICAI systems that are oriented around a group pedagogy. Such a pedagogy has been demonstrated as more effective than individual-oriented pedagogy and may in fact generalize to training situations with an emphasis on declarative knowledge as opposed to the training of complex psychomotor or motor skills. In fact, by intelligently combining observational learning, discussion groups, and competition, it may be possible to develop an ICAI based on group pedagogy that is superior to one based on individual pedagogy. It is clear research is needed in this area, to identify boundary conditions, task characteristics, and individual differences which most influence the effectiveness of individual versus group-based instruction.

ICAI and Teamwork Instruction

We expect that principles of skill acquisition and instruction validated at the individual level will generalize to the individual team member, once teamwork task demands are identified for each team member. This approach will enable systematic generation and evaluation of teamwork training principles--to predict what should be trained, to whom, in what sequence, using what type of instructional delivery, in what kind of context. Here, we describe progress towards development of a taxonomy of teamwork tasks and associated cognitive demands.

As discussed above, there are several factors that influence skill acquisition in group instruction, even when all participants are learning the same task--observational learning, discussion groups, cooperative versus competitive dynamics, and social factors. When we consider the application of ICAI systems to the training of work teams, the situation becomes even more challenging. Work teams are often comprised of members with diverse expertise, who must coordinate information, decisions, and actions in order to achieve a mutual goal.

As described above, in our program of research we have investigated the usefulness of teaching small groups to perform tasks that in the end will be performed individually. We believe, however, that pedagogy designed for individuals can be effectively applied for the training of team performance, once key issues are addressed. Individualized instruction is often developed for relatively static task environments, such as the operation and maintenance of stable systems (Lesgold, Lajoie, Bunzo, & Eggan, 1992). The knowledge required for such tasks can be captured through identification of key "if-

then” and “how to” statements. Procedures can be specified in advance, and team members need only to follow these procedures to attain coordinated performance. However, team performance often occurs in dynamic environments--indeed the pervasive use of teams by organizations is to a large extent in response to the need for more flexible and adaptive structures.

The primary challenge here is to develop instruction to enhance teamwork performance in complex and challenging situations. We must be able to identify the knowledge and skills that comprise effective teamwork in different settings, particularly those related to success in ambiguous and dynamic environments. Our approach builds upon our TRAIN (Training Research for Automated INstruction) model for individuals, extending the model to include teamwork functions. A taxonomic approach is used to characterize teamwork functions and prerequisite knowledge and skills.

Researchers at the TRAIN laboratory have developed and validated a theory-based approach to characterizing tasks that are performed by individuals. The approach has proven effective for the design of training for individually performed tasks. The approach rests on:

- (1) a General Learning Theory that specifies dimensions of knowledge and skill and corresponding characteristics of skill acquisition,
- (2) a Cognitive Taxonomy that allows reliable decomposition of tasks into knowledge/skill types that support task performance,
- (3) a General Instructional Model that specifies how acquisition of these knowledge/skill types can be optimized, and
- (4) a set of Criterion tasks that allow us to systematically conduct studies on human acquisition of these knowledge/skill types.

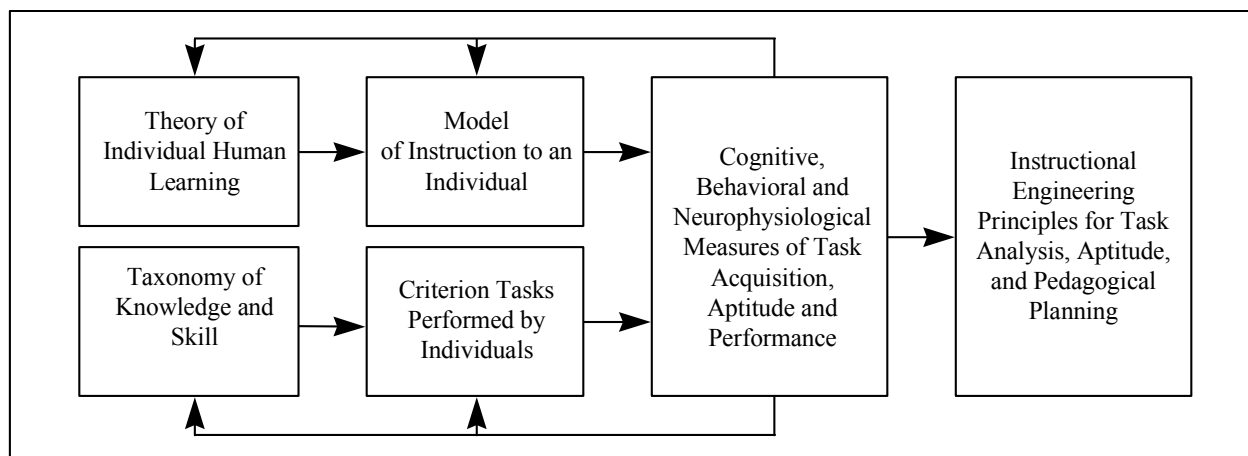


Figure 1. Instructional Engineering for Individually Performed Tasks

We are now attempting to scale our approach to individualized instructional engineering up to team-level performance. At the team level, we proposed to develop theory and taxonomies correspondent to our individual approach, to include:

- (1) a general Theory of Teamwork Performance
- (2) a Cognitive Taxonomy of Teamwork Demands
- (3) a general Team Training Model
- (4) a set of Team Criterion Tasks

Any approach to team training must deal with the relationship between individual performance and team performance. First, we must specify distinctions among individual and team-level performance constructs. What are the knowledge and skills that underlie successful team performance, and to what degree are they generalizable across categories of team tasks? To address these questions, taxonomies must be specified to generate a systematic approach relating aspects of team functions with aspects of task knowledge and skill requirements. Boundary conditions should be drawn from a taxonomy of team task characteristics. From these dimensions, propositions are made with regard to development of instructional content, drawn from extensive accomplishments in development of individualized training.

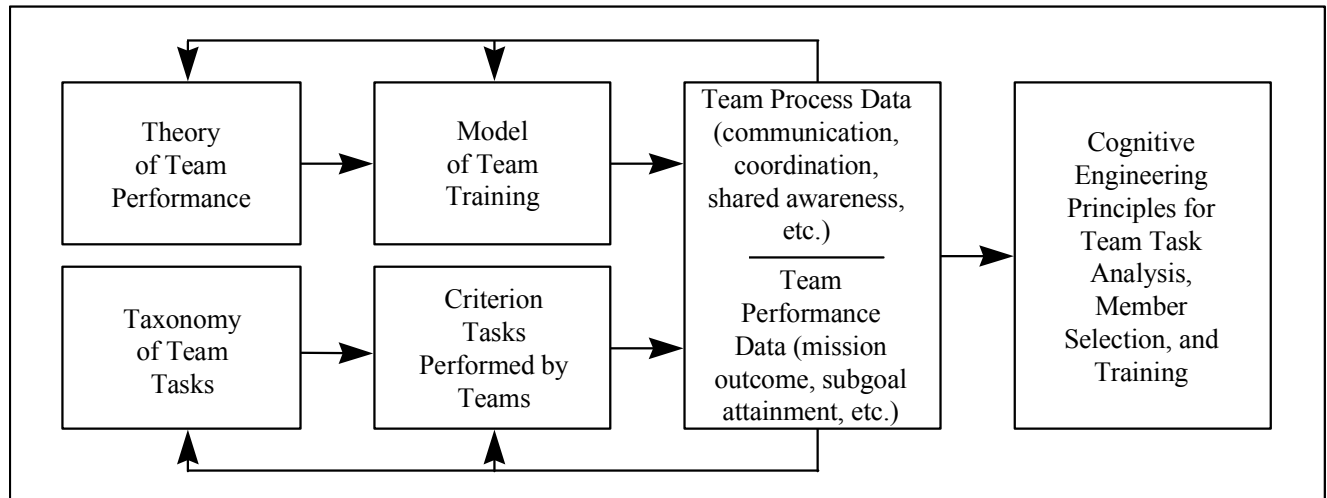


Figure 2. Instructional Engineering for Teamwork Tasks

Once theoretical constructs, relationships, and boundary conditions are identified, systematic investigations regarding optimal training of teamwork functions can be initiated. For example, should we train individual skills outside of the team task context, or simultaneously with team skills? If skills are taught as part-tasks, which skills should be taught separately, and in what sequence? Are there generic teamwork skills that can be taught using a synthetic task? What level of fidelity in synthetic tasks is required for effective training? We believe that a useful characterization of team task performance should emphasize individual task performance models for each member of the team. Team performance is ultimately an algorithm comprised of elements of individual performance.

It has been stated that an expert team is more than just a sum of its members (Salas et al., 1997); nonetheless, it is still the case that overall team performance is effectively the interplay of individuals performing in a team context. We expect team members high in task expertise who nevertheless perform poorly as a team are lacking teamwork skills, and that these skills can be trained. Skill acquisition is an individual-level phenomenon, which can be represented at the team level to compare teams, but is a function of the individual. Instructional concepts validated at the individual level should transfer to the training of teamwork skills.

This is not to say teamwork should be trained as an individual task, although much of it could be accomplished given advancements in computer-based simulations. Simulations can now present a complex environment, filled with computer-generated hostile and friendly “entities” and “advisors” (Elliott et al., in review; Schiflett & Elliott, 2000). Trainees can interact with computer-generated team

members that can vary in level of expertise, thus providing a high level of control and reduction of error. On the other hand, there is no substitute for interaction with actual people, when studying sources of error arising from the ability to “deal” with various personality characteristics and achieve effective group problem-solving, conflict resolution, and negotiation skills.

Performance requirements that apply only to individual team members (individual task expertise) will be modeled at the individual level, using our existing tools. Team level performance requirements, such as information exchange, performance monitoring, resource allocation, and/or group problem solving will be modeled at the individual level and as team-level performance constructs. While much is stated about team training and team mental models, it is useful to maintain the distinction between individual skill acquisition, expertise and performance, versus team-level constructs which are truly a function of the team as a whole, such as morale, cohesiveness, coordination, and overall performance outcomes. There are several lessons-learned with regard to conceptualization and measurement of team-level constructs, discussed at length elsewhere (James, 1982; Jones, 1974).

We draw upon the substantial work accomplished by Salas and his colleagues (Brannick, Roach, & Salas, 1993; Cannon-Bowers, Burns, Salas, & Pruitt, 1998; Cannon-Bowers & Salas, 1998; Salas, Bowers, & Cannon-Bowers, 1995; Salas, Cannon-Bowers, & Blickensderfer, 1997; Salas, Cannon-Bowers, & Johnston, 1997; Salas, Dickenson, Converse, & Tannenbaum, 1992; Swezey & Salas, 1992) for our initial starting point. Consistent with his model of team performance, we distinguish team performance as a function of taskwork and teamwork. We then propose a taxonomy of core teamwork functions that support management of team member interdependencies. Our current plan is to model team level team-task performance using a single instantiation of the Team Performance Model (currently version 1.0), and to model individual team-task performance using multiple instantiations of the TRAIN cognitive model (currently version 2.6).

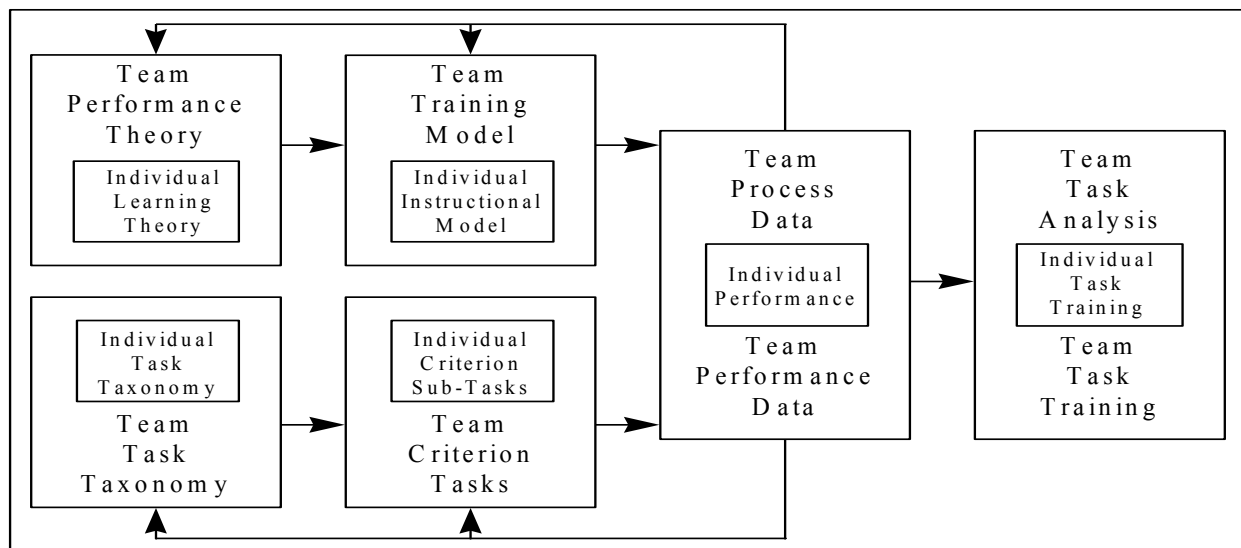


Figure 3. Instructional Engineering: Teamwork and Taskwork

To provide a starting point for team-level instructional engineering, we specify (a) an initial Team Performance Theory and (b) associated taxonomies to characterize teamwork functions, teamwork knowledge and skill requirements, and team task characteristics. These hypothesized constructs are our initial attempt to decompose teamwork tasks into discriminable functions that support task performance, which can be generalized to teams in general, and to quantify dimensions of teamwork task complexity. They constitute our first attempt at modeling team-level task performance. Our initial taxonomies of teamwork functions and teamwork demands are described in the following sections.

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Teamwork Task Demands: A Functional Approach

In dynamic situations, teamwork becomes vital: to manage interdependencies team members must maintain awareness of changes in strategic information, gained from a variety of sources. Team members are often in communication with different individuals, teams, organizational entities (such as corporate headquarters, customers, and/or competitors), and computer/equipment/decision aids. In addition, team members may have different areas of expertise, may be working on different aspects of the team goal, and may be located in different geographic locations. As a result, team members will have different interpretations of their task environment. This information should be interpreted and shared in order to identify inconsistencies, generate alternate interpretations, and discover emerging problems.

Team-based training has been shown to be an effective means to train knowledge and skill requirements for efficient coordination of information (Cannon-Bowers et al., 1998; Kozlowski et al., 1998; Swezey & Salas, 1992). Similarly, it is expected that team-based training can enhance development of adaptive expertise within dynamic contexts. In fact, there is quite a bit of overlap in investigations of complex naturalistic performance and team performance, for both are critical to the understanding of expert performance in context (Beach, Chi, Klein, Smith, & Vicente, 1997; Brehmer, 1992; 1998; Cannon-Bowers & Bell, 1997; Coovet et al., 1995; Drillings & Serfaty, 1997; Howell, 1997; Klein, 1993; 1997; Kleinman & Serfaty, 1989; Klein & Woods, 1993; Kozlowski, 1996; Kozlowski et al., 1999).

Our goal in developing the Teamwork Taxonomy is to categorize and describe team tasks at a level of analysis that supports:

- 1) Abstract descriptions of task performance
- 2) Predictions about instructional approaches that will optimize task performance
- 3) Generalizations about instructional approaches that will work across team tasks
- 4) Recommendations about team task structure and team task performance contexts
- 5) Recommendations about team member selection

A taxonomic approach is essential for systematic investigation of team performance dynamics and skill acquisition. Critical boundary conditions need to be identified as part of the theory-building process. It is evident that teams span a diverse array of functions. Several taxonomies have provided

some key distinguishing factors among these teams (Cannon-Bowers, Oser, & Flanagan, 1992; Fleishman & Zaccarro, 1992; Salas et al., 1992; 1995; Sundstrom, De Meuse, & Futrell, 1990; Swezey & Salas, 1992).

Existing taxonomies of ability requirements and task characteristics were reviewed, and each is useful for its stated purpose. However a taxonomy is needed that can be used to distinguish teams on the basis of the degree and type of teamwork needed for successful performance. This taxonomy would be used to (a) distinguish types of teams, (b) identify teamwork training needs, and (c) provide a framework for teamwork performance assessment.

Our teamwork taxonomy must effectively categorize the demands that performance of any team task makes on the team, and must allow any task to be described in terms of both team and individual capabilities that support performance in the task. Review of existing taxonomies resulted in a long and varied list of many types of behaviors (e.g., “assisting others,” “requesting help,” “exchanging information”), functions (e.g., “monitor performance of others,” “coordination of tasks”), and skills (e.g., skills which facilitate resolution of interpersonal and task decision conflicts). Many of the constructs in existing taxonomies appeared as if they may be useful for some types of teams but not others. For example, it is intuitive to expect that collaboration and conflict resolution skills would be needed in teams that have a consensual decision process, but perhaps not for teams where decisions must be made quickly by one individual. In the same way, monitoring the performance of other team members may be critical for some teams, and detrimental to others (when the information is not necessary and time is short). It seems clear that critical aspects of teamwork performance will depend on contextual factors such as task demands, information characteristics, and team structure. How then can one systematically approach various kinds of team settings and identify teamwork requirements? We began with a functional definition of teamwork, which can generalize across all types of teams and settings.

What is teamwork? We began with the definition of teams. Teams are distinguished from groups in general by a common purpose or goal, performed by interdependent team members (Swezey & Salas, 1992). From this definition we derive a core definition of teamwork, as contrasted with individual taskwork: the fundamental function of teamwork is the effective managing of interdependencies to accomplish team goal.

The sheer diversity of teams makes it difficult to identify core components of teamwork. Consider the types of teams described in existing taxonomies. What can these teams have in common in terms of how to work more effectively together? One core dimension that characterizes teams in general is the type and degree of interdependence among team members (Saavedra, et al., 1993; Swezey & Salas, 1992). Teams are distinguished from groups in general by a common purpose or goal, performed by interdependent team members (Salas, Dickinson, Converse, & Tannenbaum, 1992). From this definition we derive a core definition of teamwork: The fundamental function of teamwork is the effective managing of interdependencies to accomplish team goal. Based on this focus on team member interdependencies, we generated an initial taxonomy to distinguish team-level functioning based on type and degree of interdependence among team members. The purpose of this generic taxonomy is to serve as an overarching framework to distinguish teams in general, across performance domains, with regard to the nature and extent of teamwork demands.

A fundamental aspect of the demand for teamwork is the degree to which interdependencies exist among team members. To ascertain this one must define the nature by which team members may be interdependent in such a way that can be generalized among various types of teams. Assuming the essence of teamwork is the managing of team member interdependencies, we identified two core

dimensions with regard to nature and extent of interdependencies, that of (a) coordination complexity (static) and (b) adaptive replanning (dynamic). Each core function can be analyzed to identify tasks and task sequences necessary to accomplish functional goals (Schiflett & Elliott, 2000).

Another fundamental dimension of teamwork task demand that is expected to distinguish knowledge and skill requirements and training strategy is the nature of the decision process used to accomplish each aspect of teamwork. The team decision making process may be hierarchical, when there is a team leader who makes a final decision, or it may be dependent on consensus. If there is a strict hierarchy in the team structure, such as in most military teams, one achieves efficiency in high-tempo situations, but the team and particularly, the team leader, must be trained to perform effectively in this context. If the team decision making is more consensual, negotiation and conflict resolution skills become important and different training content and decision aiding tools would be indicated. This is particularly true if the team is comprised of specialists as opposed to generalists.

There are other dimensions that can be related to training content/delivery, but each would be associated with a subtask required to achieve underlying teamwork functions in a particular task setting and thus are not considered core. We begin with a focus on three core dimensions characterized in all team settings. They are expected to distinguish requirements for effective teamwork and training content/delivery:

- 1) Degree of Coordination Complexity
- 2) Degree of Dynamic Replanning
- 3) Type of Decision Process—Hierarchical Versus Consensus

Once the performance domain has been analyzed for these core teamwork task demands, we can generate hypotheses as to knowledge, skills, and abilities required for successful performance for both aspects, thus identifying requirements for overall team performance.

Determining Cognitive Demands: Cognitive Taxonomy of Teamwork

The model described above provides a core conceptualization of teamwork, based on three independent dimensions underlying all team tasks. Any team task can be characterized along these dimensions. Each dimension has implications for teamwork skill requirements and team training content/delivery. From this framework, functions can be identified for a particular team setting, as a first step in identifying specific subtasks and their corresponding cognitive/skill requirements. The final level of detail and specificity will depend on the purpose of data collection (e.g., identification of criterion measures, training requirements, decision support tools).

Our approach to performance engineering requires identification of underlying cognitive demands. For example, a team task may have a high requirement for coordination achieved through performance monitoring (of self and team members), information retrieval, and information exchange. The optimal instructional method to enhance these tasks would depend on the nature of the task. Performance monitoring in one team setting may be straightforward and easily acquired through repetition and practice. A different team setting may demand much more skill in information processing and require a different approach to training generalizable skills.

Once teamwork functions and tasks are identified, they can be further analyzed with regard to type and degree of cognitive demand. For example, the problem solving required by teams with high levels of dynamic replanning can be relatively easy (certain information, distinct decision rules) or challenging (uncertain information, ambiguous rules of engagement). In addition, time pressure can alter the type of

decision process used, from careful deliberation to a more satisfying, recognition-based process. The following table characterizes the cognitive demand of tasks based on information and decision process from simple to complex.

Table 3. Cognitive-Based Taxonomy of Teamwork

Task Components	1 Simple	2	3	Complex 4
INFORMATION Dynamic Information Requirements	CONCRETE No Interpretation Required	CONSISTENT Consistently Interpreted Information	CONTINGENT Situationally Consistent Interpretations	FUZZY Ambiguous Subjective Interpretations
DELIBERATION Prerequisite Shared Knowledge and Interaction Procedures	FACTS Linear Information Flow	CONCEPTS Fully Specified Branches	SCHEMATA Situationally Consistent Branches	MENTAL MODELS Fuzzy, Complex Procedures Contingencies
RESOLUTION Decision Rule Specificity Difficulty	EASY RULES Simple Fully Specified	RULES Consistent Decision Rules	CONTINGENCIES Situationally Consistent Decision Rules	EXPERT JUDGMENTS Fuzzy Decision Rules
ACTION Skill level	BASIC ABILITIES Existing Skills Low Coordination	BASIC SKILLS Specified Procedures Easily Automated	SKILLED PERFORMANCE Complex Integrated Can be trained to Automaticity	EXPERT PERFORMANCE Complex Integrated Dynamic

This taxonomy portrays facets of team information processing and decision making along a dimension of cognitive complexity. It is derived from a taxonomy generated and validated at the individual level, at the TRAIN laboratory. The taxonomy describes aspects of information processing (i.e., information retrieval and deliberation), decision making, and skill requirements. It also provides the basis by which each of these functions can be categorized with regard to complexity. Once teamwork tasks are identified, tasks can be categorized along this dimension, and propositions established at the individual level from prior research can be generalized to team-level performance.

While aspects of teamwork may be fairly consistently associated with levels of complexity and difficulty (e.g., a high degree of coordination complexity or dynamic replanning would indicate high cognitive demand), it is necessary that all teamwork tasks and subtasks within a particular context be evaluated along this dimension. It should be noted that a particular type of team task can still vary widely in complexity, depending on context, goals and expectations. As a simple example, one can easily distinguish differences along each aspect for different basketball teams. Consider the differences in cognitive and skill requirements to perform well in a volunteer company-sponsored team versus the NCAA. The goals, rules, and strategies may apply to both sets of teams, but training and performance goals are substantially different.

DISCUSSION

Our goal is to investigate skill acquisition and performance within more complex, dynamic, team-based settings. To accomplish this, we rely on advanced techniques for representation, characterization, and instruction of expert knowledge. Intelligent tutoring based on cognitive science has repeatedly proven itself for individual skill acquisition across a variety of performance domains (Regian & Wolfe, 1999). The transition to a more team-based approach will require (a) explication of teamwork tasks, based on a broad, generalizable taxonomy of teamwork, (b) knowledge elicitation techniques to enhance capture of teamwork demands in a particular setting, (c) development of synthetic environments with core characteristics which enable skill acquisition of teamwork tactics, strategies, and/or problem solving, and (d) modeling approaches which enable explication of an expert model and student models at both individual and team levels of analysis.

This becomes particularly challenging in naturalistic environments characterized by complexity, ambiguity, interdependency of events among team members, and interdependency of events over time. These challenges are well discussed elsewhere (Beach, et al., 1997; Beach & Lipshitz, 1993; Brehmer, 1992; 1998; Cannon-Bowers & Salas, 1998; Drillings & Serfaty, 1997; Lipshitz 1993; 1997; Rasmussen, 1993; Zsombok, 1997). Thus, we began with a focus on this kind of setting, with the goal of creating taxonomies, which distinguish relevant boundary conditions for investigations. We needed to articulate this kind of setting in a systematic fashion, based on existing frameworks of cognition, information processing, and cognitive demand.

A first step in this process was the identification and review of existing team research findings relevant to highly complex and dynamic operational environments. Current knowledge of teamwork performance has benefited greatly from the contributions of several researchers over the past 15 years, resulting in identification of many methodological and psychometric issues particular to team-based research (Hollenbeck et al., 1994; 1996; 1998; Salas et al., 1992, 1995, 1997; Serfaty, Entin, & Johnston, 1998). For example, while teamwork is indeed based on the interplay of individuals, the measure of teamwork is not necessarily, or even commonly, based on the sum of individual performance. Team success could be a function of the best team member, or of the worst.

The key is conceptualization and measurement of the “interplay” itself, in various contexts. Researchers have generated various taxonomies, classification/coding schemes, and theoretical models involving constructs such as team coordination, cohesiveness, collective efficacy, shared mental models, hierarchical decision processes, and team situation awareness. However, empirical validation of theoretical predictions regarding operational performance has been hampered by a lack of similarity between highly controlled laboratory team tasks and the dynamic complexities found in realistic settings. This is not to say that findings generated from laboratory settings are irrelevant; but rather that advanced platforms can be used to demonstrate generalizability of theoretical propositions to more naturalistic expert-based performance domains.

This paper described our general approach to investigate team training using principles of ICAI. First, we described theory and principles related to intelligent tutoring systems. Then, we discussed the nature of teamwork and proposed a functional taxonomy of teamwork to enable systematic classification of team task demands and dimensions of teamwork performance. This taxonomy proposed two core functions of teamwork, one static (coordination complexity) and one dynamic (adaptive replanning) and another fundamental dimension of team decision making process (hierarchical versus consensual-based processes). These dimensions are expected to distinguish teams by teamwork skill requirements, and assist in identification of training content / delivery.

Once type and level of teamwork tasks are identified, they are further analyzed using cognitive analysis techniques to determine level of cognitive complexity for each team task and subtask. To accomplish this, we delineated a cognitive taxonomy of teamwork, based on an information-processing model of cognitive demand and cognitive function. We expect that principles of instruction based on this cognitive taxonomy, proven to be successful at individual-level instruction, will transfer to the training of teamwork.

Systems are currently being developed to facilitate research in team training and performance. For example, synthetic task environments were developed to capture essential higher-level functioning of weapons directors who work aboard the Airborne Warning and Control System (AWACS) aircraft (Chiara & Stoyen, 1997; Elliott et al., 2000a, b; Mahan, 1998; Hess et al., 1999; Hess & Elliott, 2000; Schiflett & Elliott, 2000). These synthetic environments are simpler than the actual aircraft systems, which have numerous specific switch actions to accomplish a variety of actions. Instead, the synthetic tasks may be accomplished by mouse clicks and menu selections, a task already familiar to anyone who uses a PC. We presented two such systems to operational experts. While the two systems were different with regard to specific actions, the experts quickly recognized their fundamental tasks and had no problem adjusting to either interface. Procedures regarding information retrieval, communication, and decision making were quickly learned, in about five minutes. Participants were soon immersed in higher-level tactics and decision making.

The next challenge is the representation of knowledge and performance within these team-based systems, particularly in highly demanding and complex settings. In order to insert ICAI technology in these systems, we need quantitative representations of expert and student performance. An initial start in this area has been accomplished, within one of the AWACS-based systems. Intelligent agent technology was utilized to build a decision-aiding capability that provides team members with recommendations for particular decision events. These recommendations are based on representations of each type of decision task, thus comprising an expert model for those tasks. However, this system is not an ICAI system. It is more strictly a decision aid that can be utilized, or not. While additional programming is necessary to provide tutoring capability, progress toward that goal has been demonstrated. The rationale for recommendations is not available at the time it is generated; however, each decision event is logged in a

data file along with the recommendation, the rationale, and the action taken. Further refinements would provide more feedback on each decision event as it occurs.

Again, the challenge in building these systems is the representation of performance and knowledge in these complex settings. Many contributions have been made recently which relate to conceptualization and quantification of dynamic C3 performance (Benson et al., 1998; Chin, Sanderson, & Watson, 1999; Covert & Riddle, 1999; Kleinman et al., 1992; Lee & Carley, 1998; Levchuk, Luo, Levchuk, Pattipati, & Kleinman, 1999; Levchuk, Pattipati, & Kleinman, 1998; 1999; Levis & Vaughan, 1999; Paley, Levchuk, Serfaty, & MacMillan, 1999). One or more of these approaches may be the means by which expert / student performance can be represented and interpreted.

Intelligent agent technology holds much promise for on-line and off-line performance feedback and tutoring in complex environments, and many efforts are now being reported (Tecuci & Keeling, 1998; Towns, Fitzgerald, & 1998, to name just a few). However, existing difficulties in modeling expert performance in these settings leads one to the conclusion made by Salas, Cannon-Bowers, and their colleagues—pertaining to the importance of event-driven assessment of performance (Fowlkes, Lane, Salas, Franz, & Oser, 1994; Salas et al., 1997a,b,c). It is absolutely critical to develop scenarios with careful attention to research and training goals, individual and team-level constructs of performance, with well-defined manipulations, articulation of expected effects, and interpretations of behavioral responses to trigger events.

In summary, we have described progress to date in our investigations in team training and research. Further efforts will continue along the path described here. Infrastructure for team training research has been established, with regard to software, hardware, and facilities (Regian & Elliott, 2000). Propositions based on instructional principles and boundary conditions will be further explicated and tested. ICAI principles and instructional approach will be applied to team settings and embedded in team-based research systems. These efforts will not be achieved by a single researcher or research lab. Instead, we will collaborate with a number of universities and companies, as part of a multidiscipline team of teams, focused on the enhancement of computer-based training and performance in complex naturalistic settings.

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