CHAPTER 22 –Shared Mental Models of Cognition for Intelligent Tutoring of Teams

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Introduction

This chapter discusses ways ITS principles and structures found in GIFT (Sottilare, Brawner, Goldberg, and Holden, 2012) might be applied to the training of teams. It concerns using the cognitive models of team purpose, behavior, and functions that are shared – held in common – by individual team members to training for teams in a manner analogous to the use of cognitive models in ITS for individuals. We recognize that non-cognitive factors (e.g., physiological and affective) influence team performance and processes. For this chapter, however, we have chosen to focus on cognitive factors.

The use of fully automated, computer-based tutoring technologies to provide training for teams is as embryonic as the problem space is complex. A necessary step in determining optimal strategies for team learning is to assess the collective state of the team, which may be accomplished through the use of shared mental models. Empirical evidence suggests that these models, contribute substantially to successful team performance (e.g., Cannon-Bowers, Salas & Converse, 1993; Rentsch & Hall,1994; Stout, Cannon-Bowers, Salas & Milanovich, 1999; Salas & Fiore, 2004; Banks & Millward, 2007; DeChurch & Mesmer-Megnus, 2010; Espevik, Johnsen & Eid, 2011). However, the notion that shared mental models of cognition within teams might somehow be additive or averaged among team members appears untenable. If AI tutoring is to equal or perhaps exceed skilled human tutoring, success will demand more elegant and powerful approaches for assessing these models and the learning state of teams. These approaches must accurately sense and interpret the critical individual behaviors, team interactions, and environmental factors that promote/inhibit team performance.

Shared mental models represent team objectives and the actions, both individual and collective, needed to achieve them. These models represent team communication and coordination, team posture, situation, and environment, and team member roles and responsibilities. They enable team members "to interpret cues in a similar manner, make compatible decisions, and take appropriate action" (Cannon-Bowers & Salas, 2001, p. 196). Their application in the design and development of intelligent training capabilities for teams appears to be a natural and promising approach for consideration.

The motivation for developing/maintaining shared mental models of cognition is much the same as for maintaining individual models of cognition. For individuals, we refer to the adaptive tutoring learning effect chain (Figure 22-1), where selective mining of learner data (e.g., behaviors and sensor inputs) informs learner states (e.g., cognition, affect), which informs strategy and tactics selection by the tutor and ultimately influences learning gains. Better models of learner cognition result in accurate strategy selection and in improved learning (e.g., knowledge acquisition, skill acquisition).

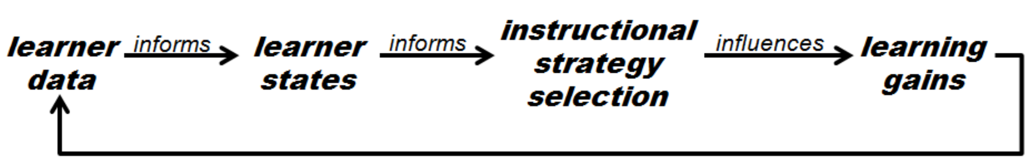

Figure 22-1. Adaptive tutoring learning effect chain (Sottilare, 2012)

When learners train as part of a group, they can encourage each other to ask questions, explain or justify their opinions and reasoning, and actively reflect on their developing knowledge and team performance. Research has shown these activities enhance group performance and individual learning outcomes (especially motivation and engagement – Tchounikine, Rummel, and McLaren, 2010). However, these benefits can only be achieved in well-functioning, actively learning teams (Jarboe, 1996; Soller, 2001). While some teams may demonstrate successful interaction and communication naturally, others may be incapable of developing a balance of participation, leadership, understanding, and encouragement (Soller, 2001). This inability can rapidly degrade group and individual performance, motivation, and engagement, and thereby learning.

As Figure 22-2 suggests an adaptive tutoring learning effect chain model could be extended for teams and then specifically adapted to focus on shared mental models of cognition.

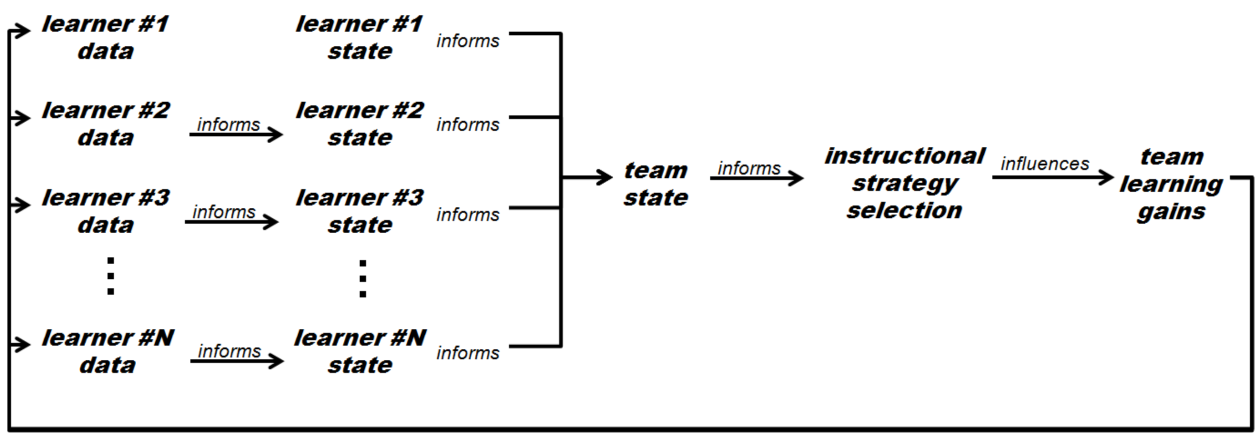

Figure 22-2. Notional Adaptive Tutoring Learning Effect Chain for Teams

Mental Models – Shared and Otherwise

Rouse and Morris (1986) identified common themes in the use of mental models. They described these models as "mechanisms whereby humans are able to generate descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions (or expectations) of future system states" (p 351). Mental models are often dynamic – acting as mental simulations.

Shared mental models may then be viewed as descriptions, explanations, and predictions that the members of a group, such as a team, hold in common. In the case of teams, they are defined by Cannon-Bowers, Salas, and Converse (1993) as "*knowledge structures held by members of a team that enable them to form accurate explanations and expectations for the task, and in turn, to coordinate their actions and adapt their behavior to demands of the task and other team members*" (p. 228).

Research on mental models intensified in the mid-1960s with the evolution of general theories of perception and learning. These theories evolved from the fairly strict logical positivism of behavioral psychology, which emphasizes the study of directly observable and directly measurable actions, to what researchers began to call cognitive psychology. Cognitive psychology gives more consideration to internal, less observable processes, which are assumed to mediate and enable human learning and thereby produce the directly observable behavior that is the subject of behaviorist theories.

Cognitive psychology opened the door to consideration of mental models, but its theoretical and empirical foundations preceded it. The notion of mental models may be found in the primordial origins of scientific psychology. For instance, William James (1890/1950) stated his General Law of Perception as the following: "*Whilst part of what we perceive comes through our senses from the object before us, another part (and it may be the larger part) always comes out of our mind*" (p. 747, 1890/1950). A mental model, then, is a mental representation of the perceived world informed, however imperfectly, by our senses.

Despite the early enthusiasm for behaviorism in experimental psychology, empirical support for a more cognitive view continued to grow. In 1967 Ulric Neisser could point to a large body of empirical evidence indicating that many aspects of human behavior, such as seeing and hearing, could not be accounted for solely by external physical cues. His central assertion was "*that seeing, hearing, and remembering are all acts of construction, which may make more or less use of stimulus information depending on circumstances*" (p.10).

Neisser's contribution helped free researchers to pursue new, more "constructivist" approaches to perception, memory, learning, and cognition by emphasizing their necessity. These approaches require an active synthesis of the environment based on a runnable cognitive model – a cognitive simulation – that is validated or modified by cues impinging on the senses. These actively evolving simulations, not the external stimuli alone, are now assumed to account for what an individual understands about the environment.

We can extend these notions to the functioning of teams. As information and data become available to teams, they are not assumed to be taken in "neat." Instead, they appear to be absorbed and integrated into a rapidly evolving collective simulation of the external environment. Team decisions then result from shared cognitive simulations that are run forward under various scenarios and parameters in order to determine optimized courses of action. Team members must therefore take responsibility for the correctness of their own models and for the ability of others to share them.

Determining how teams develop these models and/or simulations and then share their results should considerably strengthen our procedures for assessing team decision making and performance. Creative, accurate, and comprehensive mental models that take account of all salient cues and filter out others of less immediate importance appear to be critical. Rapid decision making that quickly assesses situations and selects among different decision choices may be at a premium. A large, collective working memory seems especially important for tactical teams whose performance depends on the number of cues they process rapidly and accurately.

Teams and Teamwork

As summarized by Salas and Cannon-Bowers (2000), teams may be described as groups consisting of two or more individuals who must interact with one another in order to accomplish a common task, objective, or mission. Roles and responsibilities of individual team members may be specifically assigned, or they may arise spontaneously, depending on team size, team leadership, and presence of newcomers (Guimera, Uzzi, Spiro & Amaral, 2005). These assignments include requirements for communication and coordinated action – absent such requirements these collectives could be groups but not teams. There are, of course, teams within teams – most teams are components of a larger enterprise.

Teamwork differs in the quantity and quality of communication and coordination required. For instance, an early study by Jones (1974) compared baseball, tennis, football, and basketball teams by regressing the effectiveness of individual team members onto team effectiveness and success. Jones found success to be positively associated with the effectiveness of individual members of baseball, tennis, and football teams, but not basketball teams, where success depends on more closely balanced communication, timing, and coordination among members than the other three. The greater the need for these functions, the greater the need to deal with the team as a learning unit – as a learner with its own team mental model – and a consequent greater need to develop and assess shared mental models.

The scope and character of models that team members must share, therefore, differ with team objectives, extent of teamwork required, and roles that team-members play. At some level, however, all team members and their models must share a common understanding of team processes, interactions, and objectives. The extent to which they do and whether or not it matters can be assessed by team success in performing tasks, objectives, and missions.

Training for teams must adapt to or even prepare for the self-organization and self-assembly that occur in all teams (Guimera, Uzzi, Spiro & Amaral, 2005). This preparation seems especially important for the pick-up teams that are frequently and inevitably assembled to perform military operations. Such teams initially lack the "transactive memory" developed by members of established teams. This memory contains the knowledge and skills of specific team members and an awareness of who can perform team tasks under what conditions of motivation and support (Wegner, 1986). It allows for a division of cognitive labor within a team, permitting the team's collective knowledge to exceed that of any individual team member.

Studies reviewed by Lewis and Herndon (2011) found a strong positive relationship between transactive memory and team performance. One reason for this finding may be the long noted inverse relationship between frequency of communication and the quality of team performance in reviews of collective behavior (Briggs & Johnston, 1967; Olmstead, 1992). Communications can be minimized only if the members of teams share a common understanding of the situation and what can be done by whom.

Intelligent Tutoring Systems

The definition of an ITS varies across researchers, designers, and developers and is discussed elsewhere in this volume. In accord with GIFT, an ITS may be viewed as an effort to capture in computer technology the capabilities and practices of a human instructor who is expert in both the subject matter and one-on-one tutoring.

ITS development is motivated by the empirically evident benefits of human tutoring (e.g., Bloom, 1984; Graesser, D'Mello & Cade, 2011; VanLehn, 2011) and a long-standing desire to make these benefits more widely accessible and affordable than those delivered by human tutors (Fletcher, 1992, 2009; Corbett, 2001). Another motivation for the development of ITSs grew from the recognition that although computers could be used to teach effectively, it took time and considerable expense to anticipate all possible states of the learner and program all possible instructional responses to these states. Response to both of these motivations requires a generative capability, which is a defining characteristic of ITS. Dynamic information structures and mixed-initiative in computer-based tutorial dialogue were intended to generate instructional interactions in real time, thereby relieving much of the burden and cost of authoring adaptive, individualizing instruction (Carbonell, 1970; Fletcher, 2009; Fletcher & Rockway, 1986). To an appreciable extent, an ITS should eventually become a self-authoring system. With the capability to access almost all human knowledge through the global information infrastructure, ITS capabilities may make learning affordable and universally accessible, generated on demand – anytime and anywhere (Fletcher, 2006, 2009).

As in most technologies, ITS development begins with a metaphor, i.e., producing computer systems that clone human tutors. Just as wireless telegraph led to radios, horseless carriages led to automobiles, and so on, tutor-less tutoring may evolve into something as yet unforeseen. Sooner or later the "Columbus Effect" will exert its influence, but, for current ITS development and this chapter, this metaphor may suffice.

ITS capabilities were early envisioned by Uttal (1962), Feurzeig (1969), and Carbonell (1970). They have been pursued into the present. Today ITS development suggests a future in which education, training, and performance aiding do not take place solely through prefabricated lessons and other material but are accomplished in the form of one-on-one, guided dialogues, that are generated on demand, tailored to the needs, abilities, interests, and values of individual learners, and are based on mixed-initiative conversations in which either the computer/tutor or the learner may take the initiative. Although not widely found, dialogues of this sort have been available since the 1970s (e.g., Brown, Burton, and DeKleer, 1982). Eventually, they may provide a Plato for every Aristotle, an Aristotle for every Alexander, and a Mark Hopkins for the rest of us.

ITSs can be contrasted with drill and practice programs. The latter methods were found to be very effective in achieving lower level instructional objectives such as learning arithmetic facts (Suppes & Morningstar, 1972), grapheme-phoneme correspondences in beginning reading (Fletcher & Atkinson, 1972), and foreign language vocabulary and phonetics (Van Campen, 1981).

Such rudimentary objectives are found in initial learning of practically all subject domains. They consist of discrete items, simple concepts, or straightforward procedures to be memorized and/or applied and are limited to objectives in the lower reaches of Bloom's (1956) hierarchy or the lower left-hand corner of Anderson and Krathwohl's (2001) learning space. Drill and practice programs have a strong role to play at this level. They are effective and inexpensive to design, develop, and deliver (Fletcher, 2006). They require models of the learner, but all relevant states of the learner must be anticipated at design time and pre-programmed into the system. Learner modeling in these systems is predominately pre-assigned, implicit, and static. As effective as drill and practice programs are for helping learners master domain rudiments, they are limited in getting beyond these.

ITSs are not unique in their use of learner models, but their approach to learner modeling is fundamentally different from drill and practice. ITS learner models are dynamic and generated on demand as needed by the instructional program. They are explicit, often with reference to comprehensive models of both the procedures and knowledge required to successfully attain instructional objectives. Because of their dynamic qualities, they are particularly suited to tutorial dialogue systems that must generate instructional and problem solving guidance on demand, in real time.

Development of ITSs can aim for more conceptual, abstract, and analytical objectives, where their capabilities are better used, the expense to develop them is better justified, and they are evidently more effective (cf. Feurzeig, 1969). Effect sizes from ITS studies by Grasser, et al. (2003), Person, et al. (2001), and VanLehn et al. (2005) average about 0.62 for deep learning compared to –0.02 for shallow learning (Kulik & Fletcher, 2012).

As suggested above, the subject domain rudiments needed for teamwork can be provided efficiently and effectively through individual drill and practice. Notably, much collective training of teams is provided through practice and feedback – very much in a drill and practice manner. As in individual training, team training objectives need to transcend subject domain rudiments as, for instance, Salas and Cannon-Bowers (2000) discuss in detail. To do so, requires the ability, found in ITSs, to deal with higher order team capabilities.

A specific strength of ITS is based on their generative capabilities to identify and then provide instruction that deals with unanticipated learner states of individuals as seen in the knowledge and model tracing discussed by Anderson, Boyle, Corbett, and Lewis (1990) and Anderson, Corbett, Koedinger, and Pelletier (1995). Anticipating possible learner states for teams with their varying membership, the evolving roles and responsibilities of team members, and transactive understanding of team communication and coordination, is likely to be exorbitant in both cost and time – if not impossible. This problem is partially finessed by after action reviews (e.g., Morrison & Meliza, 1999), but these occur after the fact and, despite instrumentation, are dependent on subjective impressions and recollections. ITS techniques may have much to contribute in modeling team states and applying their capabilities to develop, and adjust team training, possibly in real time. The GIFT framework may well be used to examine this possibility (Sottilare et al., 2012).

GIFT's service-oriented ITS architecture and methodology may be summarized as containing four major components:

- An interactive interface (for mixed-initiative dialogue, allowing either the learner or the computer-based tutor to initiate queries and discussion);
- An explicit model representing the knowledge and skills that form the objectives of the instruction (where we want to go);
- An explicit dynamic model of the individual learner's evolving knowledge, skills, and progress toward achieving the objectives of the instruction (where we are now); and
- Tutoring strategies that use these models to bridge the gap between the learner's current knowledge and skills and the targeted instructional objectives (getting from here to there).

These components will be familiar to most developers of ITS. GIFT's contribution is in the details of their development, its modular and service-oriented architecture, and the particular attention it pays to sensors by separating out a sensor module as a major component of its framework.

Team Training, Shared Mental Models, and Intelligent Tutoring Systems

An issue at hand is whether team training can be informed by what we have learned about developing computer tutors for individuals. This consideration suggests two obvious levels of learning. The first level concerns the knowledge and skills of individual team members. At this level and as briefly described above, a highly effective learning environment is created by one tutor working with one learner. Meta-analytic reviews by VanLehn (2011) and Kulik and Fletcher (2012) found this approach to be substantially more effective than classroom instruction where opportunities for individualized, tutorial instruction are limited. Instructional technology has made tutoring not only accessible but also affordable by imbuing computers with the capabilities of human tutors.

To an appreciable extent, team performance is a product of personnel selection. Individuals chosen for a team need to possess the levels of knowledge and skills required by their team roles and responsibilities and to complement the strengths and weaknesses of other team members. Much training for team membership may be accomplished by individual training to meet the standards and conditions of performance required by an occupational specialty and the level of skill sought within it. The capability and likely performance of a team could even be viewed as nothing more than the sum of the competencies provided by the individual training received by its members. This might be true if teams were not composed of people.

People bring a notoriously wide range of individual differences to teams. These differences are found even when people who possess formally identified competencies can be identified, located, and assigned, which, itself, is not always the case. Beyond cognitive differences, people also bring to teams different attitudes, motivations, interests, and values. These differences strongly affect a team's abilities to perform its missions. Researchers have repeatedly and empirically found that team training and team cognition transcend the sum of individual training received by team members (e.g., Stout, Salas & Carson, 1994; Liang, Moreland & Argote, 1995; Salas & Fiore, 2004; DeChurch & Mesmer-Magnus, 2010).

A second level is needed, then, to train the team as a coherent collective. Although it relies on the prior individual training of team members, collective team training remains critical to the success of nearly all teams – and particularly teams formed to carry out military operations. Thompson's (1967) hierarchy of pooled, sequential, and reciprocal interaction and Van de Ven, Delbecq, and Koenig's (1976) methods of exchange within teams suggest increasing levels of interdependence of individual team members and increasing need for coordination among those members, and thus providing insight into what the ITS must know about the type of tasks being trained.

In pooled team models (e.g., a team of painters painting rooms in a house) where there is low task interdependence, the workload of a tutor is lower. The tutor can simply track each team member's performance and sum them all to determine the team's performance (e.g., total number of rooms painted) at any given time during training. Pooled team members generally have the same skills and roles.

For sequential team models (e.g., running a relay race) where task interdependence is higher since one member must complete an action before the next one begins, the tutor can track the output/performance of the last team member in the sequence to determine the team's overall performance, and track individual performances earlier in the sequence to project overall performance. Individual team members in sequential tasks may (e.g., relay race runners) or may not (e.g., assembly line workers) have similar roles.

The ITS workload quickly ramps up as the directionality of the workflow increases. Reciprocal, or two-way workflow, means that each team member can be both a source and a recipient in the workflow. Since reciprocal team members tend to have specialized roles, workflow and thereby performance can be compromised by subtasks with longer duration than other subtasks. For example, subtask A takes team member A an average of five minutes to complete while subtasks, B and C take two and three minutes for team members B and C to complete. Assuming that the subtasks could be done in any order, team members B and C are more likely to have downtime waiting for team member A to complete a subtask. The ITS must be aware of the characteristics of the reciprocal workflow and subtasks to avoid providing feedback unnecessarily and negatively influencing the quality of the work.

The complexity increases again as directionality increases from two (reciprocal) to a multi-directional (team model). To overcome this complexity and increase the probability of success, it would be useful to have teams with members who have multiple specialties and can switch tasks during downtimes. This is not always possible. The object of training is to build new knowledge and skills. The ITS' "understanding" of the problem space and complexity is essential in developing the individuals on the team and enhancing the performance of the team. Similar to individual tutoring, team tutoring relies on a recognition of when the team is at expectation, below expectation, or above expectation.

Might ITS capabilities developed for a single tutor working with a single learner apply to multi-learner teams? Might they be applied to develop team competencies, knowledge, cognition, and performance? For teams, and in accord with Sottilare et al. (2012), these questions may be structured around GIFT modules for sensors, learners, pedagogy, and domains. In today's GIFT, modules include models and software processes to manage data, turn into information (e.g., states), and then use that information to make decisions about instruction for individuals. To extend GIFT for use with teams, we examine the existing modules (sensor, learner, pedagogical, domain) and recommend enhancements to these and rationalize the development of specific team models.

Challenges and Gaps in Developing Shared Mental Models

While there are many challenges in moving forward with team training and the development and use of shared mental models in the process, some appear especially significant. A key to establishing effective collaborative learning is the ability of the tutor to manage uncertainty and dynamic nature of team interaction and communication.

Team members come and go. Few teams work as an established unit with the same members over extended periods of time. The social interaction among team members that is necessary for trust-building will not always foster learning (Brown and Palincsar, 1989). Traditionally, trainees view learning as an independent and mildly competitive activity. Many trainees hesitate to ask for help from their peers for fear of appearing incompetent or dependent. Furthermore, peers tend to work together with the aim of simply accomplishing tasks (e.g., finding the right answers) instead of facilitating each other's learning. The probability that all trainees understand the learning material and progress as a team increases when each member understands the roles and responsibilities, and actively participates in the training process (Soller, 2001). Shared mental models of team confidence and commitment may be essential tools for ITSs to promote active participation; encourage the exchange ideas, information, and perspectives for interaction; provide real-time monitoring of individual and team participation level (e.g., interaction analysis); and manage low participation levels.

Another significant challenge is for the ITS to understand the relationship between team and individual performance and actions. Roles and responsibilities must be defined so the computer-based tutor can aggregate individual actions in a logical, weighted fashion and adapt to the team performance state. The tutor must also understand when to provide feedback to the individual team members based on positive actions (e.g., goals met) or negative actions (e.g., distracting off-task behavior).

Peer interactions (and thereby their associated mental models) may change as the training domain changes. Interactions have been found to vary enormously even within the same domain (Brown and Palincsar, 1989). One aspect that contributes to this uncertainty in trainee communication is ill-defined roles and goals, and the adeptness of the team members at switching roles and between tasks (Burton, 1998). Role identification and switching is good for social grounding and can create an environment for collaborative learning and more effective communication (Soller, Linton, Goodman and Gaimari, 1998). This indicates that the ITS might be more effective if it could develop and maintain a model of team adaptability. As the tasks and objectives become more complex, effective communication within the team becomes more important, and the ability of the team and its members to adapt may lead to a richer learning experience. An ITS should be able diagnose and redirect incorrect solution paths, divide complex tasks into sub-tasks associated with assigned individual team members, clusters of team members, and the entire team. The idea of a team tutoring system as observer, manager (decision maker), and director is evolving.

While individual behaviors are observable, a primary challenge in developing shared mental models for ITSs arises from other, unobservable cues to individual states. Stress and anxiety, which limit cognition, may manifest themselves in outwardly observable behavior by novices, but may be more veiled by experts who have learned to set aside external stressors to focus on the task at hand. This is where physiological sensors have the potential to play a significant role in cognitive state detection. For instance, electro-dermal activity (EDA) has been shown to indicate stress and anxiety (Scheirer, Klein, Fernandez, and Picard, 2002). What is needed is a mechanism to indicate the source of the stress in order for the ITS to help manage the training experience through guidance (e.g., scaffolding) and optimize the difficulty level of the training experience – in accord with Yerkes-Dodson's (1908) inverted U, Vygotsky's (1978) zone of proximal development, or similar notions for adapting difficulty to the learner.

Finally, there is the challenge of training geographically distributed teams and developing their associated mental models. Local teams have been found to learn more than geographically distributed teams (Andres, 2002; Warkentin, Sayeed & Hightower, 1997), and distributed teams exchange information less effectively than local teams (Warkentin, Sayeed & Hightower, 1997). However, with sufficient time to develop strong group relationships and become comfortable with the communication environment, dispersed teams can communicate as effectively as co-located teams (Chidambaram, 1996). The military has developed distributed simulation for training as a way to make all team training affordable and accesible. Mechanisms to develop shared mental models based on the traits and experience of individual team members would be desirable in organizations where teams are short-lived.

Enhancing GIFT Shared Mental Models for Team Training

The GIFT sensor module provides interfaces for behavioral and physiological sensors. It accepts raw sensor data, in some cases processes this data, and then uses this information to determine individual states (e.g., workload, engagement) for transfer to the learner module.

Sensor modules may be at an advantage in team training because many aspects of decision making and problem solving in teams must be carried out explicitly and can be assessed directly, whereas they are implicit and must be inferred for individual training. Collective team cognition and declarative team knowledge remain to be dealt with, but these assessments may also be facilitated by the observable and measurable actions and procedures that are generally the object of team training and the frequently observable and measureable coordination and cooperation required to perform them. Affective team states may be similarly amenable to assessment by sensors, but they and physiological states are set aside for this chapter.

The learner module uses data received from the sensor module, performance and knowledge assessments, and demographic data to determine the learner's present cognitive, affective, and competency states. This state information is sent to the pedagogical module, where states are compared to expected learner states and matched with successful practices of human tutors to determine which instructional strategy should be used next.

Representation of team states and traits in the learner module should, in turn, benefit from sensor data provided by observation of the explicit processes and explicit actions taken in team training. Using sensor module data, a computer-based tutor will be able to deal more accurately and comprehensively in creating a dynamic representation of team cognition in general, the mental models shared by all team members, and the mental models of team communication and coordination being acquired by individual team members. Moreover, the massive amounts of team member historical, demographic, trait data, along with highly granular performance data can be rapidly recorded, accessed, mined, and updated as needed, using machine learning techniques.

The pedagogical module is domain-independent. It uses learner state, performance data, and knowledge models to determine the content, order, and flow of instruction. It recommends general instructional strategies to guide the domain module's choice of domain-dependent tactics. In team training, for instance, the pedagogical module might use ITS techniques for knowledge and performance model tracing to recommend a simulation with the type of scenarios intended to develop a number of strategic, general team capabilities such as adaptability, grit, situation awareness, problem solving, communication, or coordination.

The pedagogical module, in turn, benefits from team member trait and state data compiled by the learner module. These data not only inform decisions about what, pedagogically, to do next with a team, but also how to test the performance predictions on which its prior recommendations were based. Using learner module data, a computer-based tutor will be able to create more accurate, comprehensive, and dynamic representations of team cognition in general, the mental models shared by all team members, and the mental models of all sorts that are being devised by team members and that impact team performance. Additionally, the massive amounts of team member historical and demographic trait data can be combined with highly granular performance data to be rapidly recorded, accessed, mined, and updated as needed to enhance and apply the tutorial capabilities of an ITS.

The domain module is domain-dependent. It defines and structures the instructional domain's declarative and procedural knowledge requirements. It translates the pedagogical module's strategic recommendations into domain-specific instructional tactics, which determine the content, order, pace, and feedback alternatives for presentation to the learner. For instance, it will assess and predict the learner's progress toward achieving instructional objectives.

The domain module will similarly apply ITS capabilities to learn and improve domain-specific instructional tactics as it responds to the strategic recommendations received from the pedagogical module. It will return accurate, real-time feedback to the learner module to help it model the team state, refine its representation of team traits, diagnostically assess the team's progress toward achieving its overall instructional objectives, including those recommended for emphasis by the pedagogical module, and diagnostically model the development of individual team members in fulfilling their team roles and responsibilities.

In short, the GIFT modules and their functions may in many respects perform in team training just as they do in individual training. However, there remain issues that are peculiar to team training and team cognition that require attention in using shared mental models in intelligent training for teams. GIFT's modular, distributed architecture allows for asynchronous interaction and simultaneous tutoring of individuals. This architecture allows for individual feedback in a team context where each learner's tutor communicates changes of individual state to the other tutoring agents within GIFT, thereby supporting both team level models and individual learner models. In other words, the tutor for learner A maintains information about learner A and shares it with the tutor for learners B, C, etc. and the team states (e.g., performance) so each learner has a fully informed tutor.

Sottilare, Holden, Brawner, and Goldberg (2011) considered specific and separate team state models that may be informed by individual learner models and historical team performance data that might be gathered from relevant operational and training environments. In addition to the shared mental models discussed in the previous challenge section, models of performance, competency, cognitive, affective, trust, and communications were also considered. While this chapter has focused on team cognitive factors, it is worth noting that non-cognitive factors, such as affect, morale, confidence, and physical state, which are not discussed here, moderate cognition and their effects should eventually be considered.

Team performance models, as noted above, may consist of observations of team behavior as it progresses toward one or more objectives, including their conditions and standards of performance. Team assessment techniques are crucial in developing a clear understanding of team performance. Salas, Rosen, Held, and Weissmuller (2009) argued that performance measurement works best when it captures and considers performance from multiple sources, it is tightly coupled to the action needed, it uses validated expert models to assess the performance, it directly supports learning, and it provides real-time corrective feedback. Individual and team assessments analyze factors including (1) when each learner is ready to take an action, (2) delay in actually taking that action, and (3) value of the actions taken.

Team competency models may be used to predict performance within a domain. They are based on previous related experiences and associated levels of success. Cumulative team competency models are needed for the ITS to choose initial training scenarios and set expectations for performance. Team learning objectives, individual state information, the interactivity of the training task, and the interdependence of workflow can be used to inform a team cognitive state model that assesses mental workload, engagement and compares progress with expectations to determine team and individual strategies and tactics.

While not specifically targeted in this chapter, modeling of team affect is necessary for optimizing cognitive performance. Behavioral observations may be a pathway to understanding individual and team affect, but more evidence is needed. What is clear is that affect is a moderator of cognition. Problem solving and decision making become more difficult as affect becomes more extreme. A shared mental model of affect can inform the ITS to take action to guide, mediate, or challenge team members to get them back on track.

In accord with Olmstead (1992), among others, the amount and type of communication is considered a significant behavioral indicator of team trust and cooperation for our notional shared mental model. Roles (e.g., leader, follower, domain expert) should also be considered a factor in that roles moderate/indicate communications and expected communications. For example, a team leader would be expected to communicate mission intent (goals), clarify roles, and direct activities as needed. The ITS managing the shared mental model of cognition would be expected to monitor communication to determine how it met or did not meet expectations.

Next Steps

Salas and Cannon-Bowers (2000) chose to emphasize 10 critical questions in their comprehensive chapter on team training. They assert that ITS have great promise for team training and performance measurement, which leads to question 5 in their list, “Can intelligent systems be developed to assess, diagnose, and remediate teamwork?” (p. 331). They go on to focus on dynamic assessment, a real-time assessment capability that provides immediate feedback and automated diagnoses of performances. This thought leads to question 6 in their list, “Can mechanisms of dynamic assessment be developed for teams?” (p. 331).

In applying what we have learned from ITSs to the development of team competencies, an obvious first issue to address is how to extend ITS techniques for modeling an individual learner to modeling teams and team cognition to determine what a team “knows.” Such an extension may do much to inform GIFT learner modules and decisions made by its pedagogical modules, as they are applied to team training,

Much discussion along these lines concerns declarative and procedural knowledge (e.g., Banks & Millward, 2007). Research in the service of ITSs and elsewhere has given us tools for assessing both. For example, ITS designers often use concept models to assess what a learner and teams must know in order to achieve learning objectives (Cooke, Salas, Cannon-Bowers & Stout, 2000). These concept models have tended to bundle declarative and strategic knowledge together -- there may be reasons to separate the two into separate concept models, but that seems best set aside for the moment.

Further, much ITS activity consists of problem-solving exercises in which the progress of learners toward problem solutions can be explicitly and objectively observed (Kulik & Fletcher, 2012). ITS designers employ procedural models that lay out the actions an expert might use to solve a problem in the subject domain. Based on a learner's actions in solving a problem, an ITS can thereby infer what the learner knows. Bayesian techniques, for example, are currently prominent in such inferences. They turn cause and effect on its head, allowing us to estimate the probability of a given cause (e.g., a component of the knowledge model) that brought about the observed effect. These estimates improve as experience with additional learners build up, allowing the learning system itself to learn.

ITS tracing activities (mapping actions taken unto procedure models and inferred knowledge onto knowledge models) lend themselves well to team training, much of which involves exercises and problem solving – practice with feedback. We might apply ITS modeling and model tracing processes to teams in two ways – to identify and assess the declarative (including strategic) knowledge of individual team members and to do the same for the team itself as a collective. Empirical study on both as they apply to the training of teams and accessing their progress toward targeted instructional objectives may do much to develop ITS capabilities for team training. It would answer some long-standing questions.

For instance, in team exercises we have objective data on the performance of individual team members and of the team as a collective. ITS capabilities for inferring the knowledge element could then be used to determine the knowledge models of individuals, the collective knowledge of the team, and how the two compare. They could help determine if there is team knowledge or cognition that is separate from the sum of the mental models of its members, but the nature of this separate, collective model, how it contributes to successful performance of team tasks and missions, and what, if anything, can be done to develop it through training.

A second issue that might be addressed concerns what must be shared among the mental models of team members. Given the research on transactive memory, which is discussed earlier in this chapter, and its evident contributions to successful team performance, it appears that not all team members must possess all team knowledge. This is not a surprising conclusion, but research on team and team member cognition (or mental models) may identify what must be shared, the priorities for sharing whatever separate elements are identified, and, again, what can and should be done about them in team training, which is typically given limited time and resources.

A third issue concerns generic teamwork knowledge and skills that are separate from subject domains and must be acquired by individuals if they are to perform as successful members of a team. Most of this knowledge and skill is acquired in team training environments, which tend to be more expensive and logistically difficult to implement than individual training environments. Significant efficiencies and economies may be realized if at least some knowledge and skill in teamwork can be developed through individual training. That these competencies can be improved through individual training seems likely, but the nature and characteristics of these competencies must be more precisely identified and understood.

A fourth matter concerns the tutorial dialogues that are the eventual target for ITS development. These dialogues seem likely to remain at the individual level, but computer-based tutors could have full access to team exercise instrumentation data, provided by the GIFT sensor module, individual history and other team-relevant information provided by the GIFT learner model, training objectives held in the pedagogical model, and domain-specific data obtainable from the domain module. These dialogues could initially provide private, individualized feedback to team participants. Capabilities to do this are well within the state of the art. Eventually these dialogues might become genuine facilitated discussions with an individual. A research task with fairly rapid return may be to link up ITS dialogue capabilities with team exercise data and provide these as individual feedback. Doing so will extract much more value from training exercises than is now possible because of their accurate and comprehensive access to data and their ability to interact privately with each participant as an individual team member.

Final Thoughts

Other questions, as well as other lines of research, may well occur to readers. As Salas and Cannon-Bowers (2000) suggest, there may be much in the ITS world of value if it is applied to team training. This chapter has focused on mental models and their sharing in team cognition, but many other paths also seem likely to return significant value. Cannon-Bowers and Salas (2001) point out a number of fundamental questions to be addressed by empirical study of shared mental models including determinations of what must be shared, what we mean by sharing, how we should measure it, and what outcomes and value can be expected if we are successful. Our suggestions only begin to fill out the GIFT framework with the specifics needed. Other pathways are available and might well be pursued.

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