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# Domain Modeling for Adaptive Training and Education in Support of the US Army Learning Model—Research Outline

by Robert Sottilare, Anne Sinatra, Michael Boyce, and Arthur Graesser

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**14. ABSTRACT**

While human tutoring and mentoring are common teaching tools, current US Army standards for training and education are group instruction and classroom training, also known as "one-to-many" instruction. Recently, the US Army has placed significant emphasis on self-regulated learning (SRL) methods to augment institutional training where Soldiers will be largely responsible for managing their own learning. In support of the US Army Learning Model (ALM) and to provide affordable, tailored SRL training and educational capabilities for the US Army, the US Army Research Laboratory (ARL) is investigating and developing adaptive tools and methods to largely automate the authoring (creation), delivery of instruction, and evaluation of computer-regulated training and education capabilities. A major goal within this research program is to reduce the time and skill required to author, deliver, and evaluate adaptive technologies to make them usable by a larger segment of the training and educational community. This research includes 6 interdependent research vectors: individual learner and unit modeling, instructional management principles, domain modeling, authoring tools and methods, and evaluation tools and methods. This report (1 of 6 interdependent research outlines) focuses on domain modeling research for adaptive training and education with the goal of guiding learning in militarily relevant training and educational domains.

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# 1.  Introduction

Training and education tools and methods must be of sufficient intelligence to understand the needs of individual learners and units of learners, to mitigate negative learner states, and to guide and tailor instruction in real-time to optimize learning. These tools and methods must also be affordable, effective, and easy to access and use. These requirements are enablers of the US Army Learning Model (ALM), which includes an emphasis on self-regulated learning (SRL) where Soldiers are expected to manage their own learning and career development through the growth of metacognitive (e.g., reflection), self-assessment and motivational skills (Butler and Winne 1995). While SRL skills are difficult to train and develop, support may be provided to the learner through "adaptive training technologies" (tools and methods), which may be focused to guide learning and reinforce SRL principles.

To support ALM, the US Army Research Laboratory (ARL) has developed a program of research called "adaptive training", which includes 6 interdependent research areas or vectors: individual learner and unit modeling, instructional management principles, domain modeling, authoring tools and methods, evaluation tools and methods, and architectural and ontological support for adaptive training. The reports documenting these vectors expand the scope of the adaptive tutoring research described in ARL-SR-0284 (Sottilare 2013) to support ALM requirements in the mid-term and long-term evolution of training and educational technology: the Synthetic Training Environment (STE) and the Future Holistic Training Environment for Live and Synthetic (FHTE-LS).

This report (1 of 6 interdependent research outlines) focuses on domain modeling research for adaptive training and education. Today, the majority of intelligent tutoring systems (ITS's)—a form of adaptive training tool to support one-to-one computer-based instruction—support well-defined domains in mathematics, physics, and software programming. Since Soldiers operate in more complex, dynamic, and ill-defined domains, it is necessary to expand the scope of adaptive training tools and methods to support training and education in these militarily relevant domains. Domain modeling is a representation of knowledge for a particular task or concept and includes: domain content (a library of scenarios, problem sets, or knowledge components); an expert or ideal student model with measures of success and a library of common misconceptions; and a library of tactics or actions (e.g., questions, assessments, prompts, and pumps) that can be taken by the tutor to engage or motivate the learner and optimize learning.

## 2.   Research Goals and Objectives

The goal of the research described in this report is to model militarily relevant training domains to support individually tailored and intelligently guided training experiences as prescribed by the US Army Learning Model (US Army Training and Doctrine Command 2011). The research provides guidelines, best practices, tools, models, and methods in support of this research goal. More specifically, we desire to:

- Understand and model the characteristics, similarities, and differences of US Army training **domains** (cognitive, affective, psychomotor, social, and hybrid) with respect to their associated knowledge representations to support more efficient and effective authoring, instruction, and evaluation of adaptive training tools and methods.

- Understand and model the **dimensions** (definition, complexity, and dynamics) of training domain representations to extend the capabilities of traditional ITS's; thereby, support challenging, militarily relevant training domains.

This report examines the background and requirements for adaptive training capabilities in different domains along with research challenges, dimensions of domain modeling, desired end states, and finally, interdependencies with other adaptive training research vectors.

## 3.   Background

While human tutoring and mentoring are common teaching tools, current US Army standards for training and education are group instruction and classroom training— also known as one-to-many instruction. Group instruction and classroom training have been generally focused on acquiring and applying knowledge in proxies for live training environments (e.g., desktop simulations, virtual simulations, constructive simulations, and serious games).

Classroom training, especially for complex topics, is often taught as a series of lists that the instructor goes through in a linear fashion (Schneider et al. 2013). This approach puts a heavy burden on the learner to build mental models and make conceptual connections. Using this instructional methodology may lead to varying degrees of success due to individual differences in skills, traits, and/or preferences. More complex, ill-defined, or dynamic tasks may be difficult to instruct in a classroom environment especially if the cognitive elements of the task require spatial interaction to develop/maintain skills (e.g., marksmanship).

Small group instruction in live environments has also been used to assess application of knowledge and the development of skills. A standard feedback mechanism for US Army training is the after-action review (AAR) where significant decision points and actions are captured for small group discussion that is conducted after the completion of a training event to help capture teachable moments and to aid Soldiers in reflecting on their recent training experiences.

Both classroom training and small group instruction are manpower intensive; requiring teachers, mentors, and support staff to guide the Soldier's experience. Today, ITSs primarily guide learner training and education for cognitive tasks in well-defined domains (e.g., problem solving and decision-making tasks in mathematics and physics). Soldiers tend to perform cognitive, affective, psychomotor, and social tasks in both well-defined (e.g., building clearing) and ill-defined domains (e.g., leadership, resource allocation). ITSs generally provide static training (e.g., sitting at a desktop computer to train on a serious game) that falls short in matching the dynamic nature of many US Army operational tasks (e.g., psychomotor tasks); and thereby, reducing opportunities to develop and transfer skills to the operational environment.

Research is needed to understand the characteristics, similarities, and differences of US Army training domains (i.e., cognitive, affective, psychomotor, social, and hybrid) to develop efficient and effective adaptive training and educational tools and methods that support self-regulated learning in complex, ill-defined, and physically dynamic military domains.

## 3.1 Self-Regulated Learning and the US Army Learning Model

In 2011, the US Army placed significant emphasis on the development of SRL skills with the expectation that new methods of instruction (e.g., ITS's) would augment institutional training (i.e., classroom and small group instruction). One-to-one human tutoring has been shown to be significantly more effective than one-to-many instructional methods (e.g., traditional classroom instruction: Bloom, 1984; VanLehn, 2011). However, it is not practical nor is it affordable to have 1 expert human tutor to mentor each Soldier in the US Army for every required operational task. This alone signals the need for capabilities to support one-to-one, tailored training, and educational experiences.

Additionally, under the ALM, Soldiers are largely responsible for managing their own learning, but SRL skills are difficult to train and develop (Butler and Winne 1995; Azevedo et al. 2009; Graesser and McNamara 2010). We anticipate adaptive training tools and methods will fill this gap and will provide personalized guidance to acquire, apply, retain, and transfer knowledge and skills to the

operational environment. This signals the need for a computer-regulated learning strategy to augment missing SRL skills; however, adaptive training technologies must first become affordable, sufficiently adaptive, and easy to use for this strategy to be realized.

## 3.2  Motivation for Research

A promising alternative to one-to-one human tutoring is one-to-one adaptive training tools that include ITS's. Meta-analyses and reviews support the claim that ITS technologies routinely improve learning over classroom teaching, reading texts, and/or other traditional learning methods. These meta-analyses normally report effect sizes (sigma [$\sigma$]), which refers to the difference between the ITS condition and a control condition in standard deviation units. The reported meta-analyses show positive effect sizes that vary from $\sigma = 0.05$ (Dynarsky et al. 2007) to $\sigma = 1.08$ (Dodds and Fletcher 2004), but most hover between $\sigma = 0.40$ and $\sigma = 0.80$ (Ma et al. in press; Fletcher 2003; Graesser et al. 2012; Steenbergen-Hu and Cooper 2013, 2014; VanLehn 2011). Our current best meta-meta estimate from all of these meta-analyses is $\sigma = 0.60$. This performance is comparable to human tutoring, which varies from between $\sigma = 0.20$ and $\sigma = 1.00$ (Cohen et al. 1982; Graesser et al. 2011), depending on the expertise of the tutor. Human tutors have not varied greatly from ITS's in direct comparisons between ITS and trained human tutors (Olney et al. 2012; VanLehn 2011; VanLehn et al. 2007).

Graesser et al. (2015, in press) are convinced that some subject matters will show higher effect sizes than others when comparing any intervention (e.g., computer trainers, human tutors, group learning) to a control. It is difficult to obtain high-effect sizes for literacy and numeracy because these skills are ubiquitous in everyday life and habits are automatized. For example, Ritter et al. (2007) reported that the Cognitive Tutor for mathematics has shown an effect size of $\sigma = 0.30$–$0.40$ in environments with minimal control over instructors. Human interventions to improve basic reading skills typically report an effect size of $\sigma = 0.20$. In contrast, when the student starts essentially from ground zero, such as many subject matters in science and technology, then effect sizes are expected to be more robust. ITS's show effect sizes of $\sigma = 0.60$–$2.00$ in the subject matters of physics (VanLehn 2011; VanLehn et al. 2005), computer literacy (Graesser et al. 2004; Graesser et al. 2012), biology (Olney et al. 2012), and scientific reasoning (Millis et al. 2011; Halpern et al. 2012). As a notable example, the Digital Tutor (Fletcher and Morrison 2012) improves information technology by an effect size as high as $\sigma = 3.70$ for knowledge and $\sigma = 1.10$ for skills. The effect size attributed to improved instruction and improved domain knowledge have not been

separated in this analysis. Such large effect sizes would never be expected in basic literacy and numeracy.

Overall, these are promising results and equate to an increase of about a letter grade improvement over traditional classroom instruction. While ITS's are a promising technology to support adaptive training for individuals in well-defined domains like mathematics, physics, and computer programming, the US Army requires the ability to develop and exercise Soldier skills in more ill-defined domains (e.g., leadership) and at the unit level (e.g., collaborative learning and team training). Developing and maintaining the ability to make effective decisions under stress and in complex environments is also desirable.

Adaptive systems by their nature require additional content and complexity to support tailored learning for each user and as a consequence have a very high development cost, a major barrier to adoption by the US Army. Adaptive systems are also insufficiently adaptive to support tailored, self-regulated training and educational experiences across a broad spectrum of military tasks as required by the ALM. Today, few ITS authoring tools are generalized across all of the domains requiring training and no evaluation criteria or standards have been developed to promote reuse and interoperability among ITS's (Sottilare et al. 2012b). In other words, current adaptive systems are not yet intelligent enough to support the tailored instruction required by the US Army in the breadth of domains being trained; but there is a stable foundation of 50 years of science on which to grow an adaptive training and education capability for the US Army.

## 3.3 Adaptive Training and Education Definitions

In support of the ALM and affordable adaptive training and educational capabilities for the US Army, ARL is investigating and developing adaptive tools and methods. A desired end-state is the automation of authoring (creation) processes, instruction, and evaluation of computer-regulated training and education capabilities to help build SRL skills and support mixed-initiative interaction. A major goal within this research program is to reduce the time/cost and knowledge/skill required to author, deliver, and evaluate adaptive technologies to make them usable by a larger segment of the US Army training and educational community.

Adaptive training and education research includes elements of adaptive tutoring, distributed learning, virtual humans, and training effectiveness evaluation. For additional detail on research specific to ITS's, refer to ARL-SR-0284 (Sottilare 2013). Definitions are provided for this section to distinguish between adaptive training and education elements and also to highlight their relationships:

**Adaptive Tutoring** – also known as intelligent tutoring; tailored instructional methods to provide one-to-one and one-to-many computer-guided experiences focused on optimizing learning, comprehension, performance, retention, reasoning, and transfer of knowledge and acquired skills to the operational environment.

**Adaptive Tutoring Systems** – also known as ITS's; the mechanism or technologies (tools and methods) to provide tailored training and educational experiences; adaptive tutoring systems respond to changing states in the learner and changing conditions in the training environment to optimize learning; adaptive tutoring systems anticipate and recognize teachable moments.

**Virtual Humans** – artificially-intelligent visual representations of people that simulate or emulate cognitive, affective, physical, and social processes.

**Distributed Learning** – concurrent distribution of training and educational content to multiple users at the point-of-need in which content is intelligently selected to support learning, increased performance, and long-term competency in selected domains.

**Training/Learning Effectiveness** – evaluation of the impact of training and educational tools and methods on usability, learning, comprehension, performance, retention, reasoning, and transfer of knowledge and acquired skills to the operational environment.

**Adaptive Training and Education Systems** – a convergence of ITSs and external training and education capabilities (e.g., serious games, virtual humans, simulations) to support engaging experiences with reduced need for authoring (Sottilare 2015).

**Generalized Intelligent Framework for Tutoring** (GIFT) (Sottilare et al. 2012a; Sottilare et al. 2013a) – an open-source, modular architecture whose goals are to reduce the cost and skill required for authoring adaptive training and educational systems, to automate instructional delivery and management, and to develop and standardize tools for the evaluation of adaptive training and educational technologies.

Adaptive training and education research at ARL is being conducted across 6 interdependent research vectors: individual learner and unit modeling; instructional management principles; domain modeling, authoring tools and methods; evaluation tools and methods; and architectural and ontological support. This report (1 of 6 interdependent research outlines) focuses on domain modeling research for adaptive training systems with the goal of guiding learning in militarily relevant training and educational domains.

Soldiers operate in a variety of complex, dynamic, ill-defined domains where their ability to persevere in the face of adversity, adapt to their situation, collaborate, and think critically are key to the successful completion of their assigned missions. In order to develop and exercise these skills, it is paramount for Soldiers to train in challenging environments. Presently these few challenging training environments have been largely provided through manpower-intensive methods or systems with little ability to adapt instruction to support their learning needs. To illustrate this point Franke (2011) asserts that through the use of case study examples, instruction can provide the pedagogical foundation for decision-making under uncertainty. However, this approach is limited in implementation by the expanse of potential cases that would need to be consistently updated and maintained to support large populations like the US Army.

As noted previously, adaptive systems like ITS's have been shown to be effective in promoting learning in primarily static (e.g., learners seated at desktop computers) instructional settings within relatively simple, well-defined domains (e.g., mathematics, physics) for individual learners. For our purposes, static instruction includes cognitive, affective, or social training tasks where a desktop computer delivers instruction and where the physical movement of the learner is limited to activities that can be conducted while seated. For example, static instruction can effectively support cognitive tasks involving decision-making and problem-solving, but are less effective for training tasks involving motion and perception (e.g., land navigation and marksmanship). Ideally, we desire portable adaptive instructional capabilities to go with Soldiers to support training and education at their point-of-need across a wide spectrum of US Army operational tasks. Research is needed to develop tools and methods to support broader domain modeling, which is representative of the full spectrum of US Army operational tasks. Standards, interoperability, and automation (e.g., automated scenario generation) (Zook et al. 2012) will likely play a significant role in making adaptive training practical. In this way adaptive training technologies will have the greatest impact on organizational learning in the US Army.

## 4. US Army Requirements for Adaptive Training Systems and Domain Modeling

The Army Science and Technology community uses Warfighter Outcomes (WFOs) as the authoritative source for identifying Warfighter needs. WFOs are used to share research and future technology solutions. In the training and education (T&E) domain, the adaptive T&E research program is targeting 4 specific requirements to support the evolution of US Army training: adaptive

training and education systems; big data; training at the point-of-need; and artificial intelligence.

## 4.1 Adaptive Training and Education Systems and Domain Modeling

The primary gap to be addressed under this US Army requirement is the lack of adaptive systems (e.g., intelligent tutors) to support individual and collective (team or unit) training. The US Army needs an adaptive training and education capability that is persistent and easy to use/access with minimal startup time. There are also requirements to automate an informal AAR (also known as a postexercise critique) to reduce the time and skills needed to produce the AAR and improve its focus and quality. Another line of thought notes that the artificial intelligence in ITS's could be used to facilitate rapid mission planning and course-of-action analyses as a job aid in operational contexts.

The major connection between the adaptive training and education requirement and the domain modeling research vector is the need to extend adaptive system architectures to support instruction in relevant military domains. Affordable solutions to support adaptive training in more complex, ill-defined, and dynamic domains will more closely align training and operations, thereby resulting in more efficient transfer of knowledge and skills.

## 4.2 Big Data and Domain Modeling

The primary gap to be addressed under this US Army requirement is that there is a lack of capability to handle and process large amounts of structured and unstructured data (also referred to as big data). One capability needed is a structured data analytics program linking individual data (e.g., achievements) to required long-term competencies in military occupational specialties (MOS's). This would allow Soldiers to understand where they rank in terms of experiences and achievements among other Soldiers in their MOS. It would also allow the US Army to identify specific experiences among successful Soldiers in that MOS and provide a model for other Soldiers in that MOS to follow. The data could also be used by course managers and instructors to continuously improve instruction and the mental models of both human and computer-based instructors. Finally, data collected on trainee learning and performance during adaptive training experiences could be used to facilitate Unit Training Management (UTM) where unit commanders would have access to empirical data to support unit training decisions.

The major connection between the US Army's big data requirement and domain modeling is ability to collect learner data, learner states, and training environment data to make the connection between domain-specific instructional tactics and their varying degrees of effectiveness given instructional context (existing conditions). This will allow course managers to identify best practices over time and to promote agile configuration management of instructional content, and effective strategies, tactics, and techniques.

## 4.3 Training at the Point-of-Need and Domain Modeling

The primary gap to be addressed under this US Army requirement is the lack of an easily accessible, persistent, cost-effective, and low-overhead training environment. A capability is needed to bring training to Soldiers instead of Soldiers going to fixed training locations. This point-of-need training capability would be easily distributed, web-based, and built upon open-enterprise architecture in the cloud. US Army training and educational opportunities would be available on demand anywhere and anytime. However, it should be noted that the delivery mechanism (e.g., laptop computer, mobile device, and smart glasses) for adaptive training is critical in determining the limitations of the domain model scope and complexity. For example, it may be extremely difficult to train all the complexities of a psychomotor task in a desktop computer setting.

The major connection between point-of-need training and domain modeling is the practicality of extending adaptive training beyond the desktop. Low-cost commercial tools (e.g., smart glasses) must be investigated to determine their suitability to support the same kinds of tutor-user interaction afforded in static desktop applications. The cloud architecture to support adaptive training and education will be required to operate with and without Internet connectivity depending on the location of the learner and their access to the network. For example, if a Soldier decides to take a 2-hour (h) training course while traveling and knows that Internet connectivity will be intermittent, he might decide to download the course to his device and take it offline. The architecture must be able to track the Soldier's progress and upload results when connectivity is again available.

## 4.4 Artificial Intelligence (AI) Capabilities and Domain Modeling

The primary gap to be addressed under this US Army requirement is that the US Army lacks an automated capability to replicate the complexity and uncertainty of the operational environment. This gap specifically points to the lack of adaptiveness in virtual humans, intelligent tutoring systems, and other training

capabilities. This gap leads to Soldiers developing training-response strategies that result in less challenging training over time along with lower engagement and lower levels of learning and transfer of skills to more challenging operational environments.

The major connection between AI capabilities and domain modeling involve the discovery and innovation of techniques to support a concept called, "automated scenario evolution". AI capabilities are needed to support automated scenario evolution where AI drives the generation of new "child" scenarios from a single-parent scenario based on dimensions of that scenario and the state of the trainee. In this way, the authoring burden for highly complex training and educational domains may be reduced.

For example, consider a single scenario where dimensions include variable challenge levels based on 3 threats (i.e., low, moderate, high), 3 types of field-of-view (i.e., narrow, moderate, and wide) and clear line-of-sight (i.e., near, moderate, and far). AI could spawn 27 new child scenarios based on combinations of these variables. This requirement is closely linked to adaptive training capabilities described in Section 4.1 of this report and the realization of this capability will enable the development of affordable self-authoring adaptive systems. Through this capability, complex domains may be modeled for adaptive training systems without the need for long development cycles or special authoring skill sets.

AI-based capabilities in adaptive training and education systems may also support data acquisition (sensing), natural language, problem-solving strategies, and perceptual/interaction mechanisms in the tutor.

## 5.    Understanding the Dimensions of Domain Modeling

There are 4 typical elements that compose ITSs, a prime example of an adaptive training and education system: a learner or trainee model, an instructional or pedagogical model, a domain model, and some type of user interface. The domain model typically includes an expert or ideal student model by which the adaptive system measures/compares/contrasts the progress of the learner toward learning objectives. The domain model also includes the training environment, the training task, and all of the associated instructional actions (e.g., feedback, questions, hints, pumps, and prompts), which could possibly be delivered by the adaptive system for that particular training domain. Typical interaction between the learner, the training environment, and the adaptive system (tutoring agents) is shown in Fig. 1.
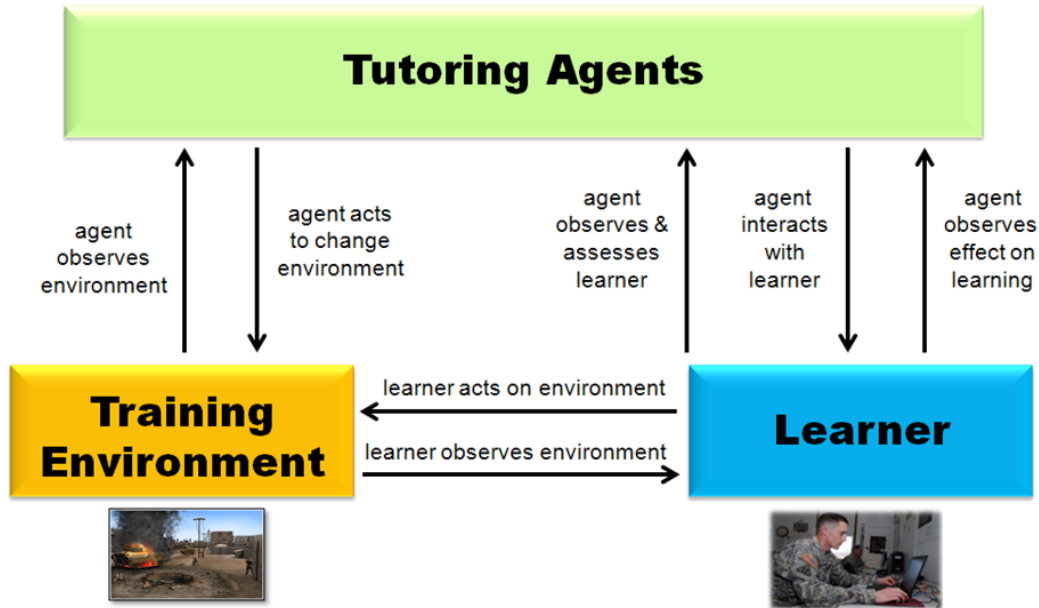
**Fig. 1    Adaptive training interaction**

Typical training systems examine the interaction between the learner and the training environment to measure progress toward learning objectives. The learner acts on the environment (e.g., opens a door or makes a choice to move into the room or stay outside) and then observes any changes or reactions within the environment. Adaptive systems add a layer of software-based tutoring agents that are designed to guide the learner in much the same way as a human tutor interacts with a learner. The tutoring agents observe the behaviors of the learner to assess their states (e.g., performance and attitudes) and interact with the learner to provide support, direction, and instruction. In addition, they track the effect of interactions on learning. Tutoring agents also interact with the training environment and may manipulate the environment to present more challenging or less challenging scenarios in response to the assessed state of the learner.

One method to describe or model the domain is by the type of task that is being trained. A traditional methodology of categorizing tasks is Bloom's (Bloom and Krathwohl 1956) Taxonomy, which describes hierarchically ordered skills (competency) in the cognitive task domain. Due to the contributions of others, Bloom's original taxonomy has evolved over time to include an affective (Anderson and Krathwohl 2001), psychomotor (Simpson 1972), and a social hierarchy (Soller 2001; Sottilare et al. 2011). The following sections describe each task domain and its relationship to adaptive training and education.

## 5.1 Cognitive Domain

Sometimes called the "thinking" domain, tasks in this domain stress the learner's thinking capacity (i.e., working memory, executive control, workload management, multitasking), problem-solving and planning, decision-making, comprehension, reasoning, and attentional focus or engagement. The determination of cognitive skills may be based on learner behaviors to indicate increases in complex and abstract mental capabilities (Anderson and Krathwohl 2001).

A revision of Bloom's Taxonomy (Anderson and Krathwohl 2001) tracks a series of behaviors from low to high cognitive skills: 1) **remembering** – the learner's ability to recognize and recall information, 2) **understanding (also known as comprehension)** – the learner's ability to organize, compare, and interpret information, 3) **applying** – the learner's ability to use information to solve problems, 4) **analyzing** – the learner's ability to examine information and make inferences from that information, 5) **evaluating** – the learner's ability to use information to make optimal judgments, and 6) **creating** – learner's ability to build new models (e.g., plans) from information.

Most of the ITS's in existence today focus on the cognitive-task domain (Anderson et al. 1995; Ritter et al. 2007; Graesser et al. 2012). Examples include model-tracing (also called example tracing) tutors that use a set of steps to walk the learner through the process of solving a problem (Koedinger et al. 2012). Mathematics, physics, and software programming are the most common types of model-tracing tutors. These domains constitute simple procedural tasks and are usually rule-based.

Matthews (2014) notes organizations generally do a good job of training relatively simple skills. However, a more challenging goal is to teach higher order cognitive skills such as decision-making and judgment. The US Army has large investments in partial-task and scenario-based training systems that use relatively fixed strategies to guide the learner based primarily on individual and team performance measures. A concern with these systems is that Soldiers learn how to win within the constraints of the system but the effect on retention and transfer is not well understood. Research is needed to build adaptivity into these training systems and thereby optimize deep learning. A goal of this research is to reduce the time to competency to allow time for automaticity through overtraining and deeper learning experiences that transfer to the operational environment.

## 5.2 Affective Domain

Sometimes called the "feeling" domain, tasks in this domain are intended to develop emotional intelligence or skills in self-awareness and growth in attitudes, emotion, and feelings. The goal is to manage emotions in positive ways to relieve stress, communicate effectively, empathize with others, overcome challenges, and defuse conflict (Goleman 2006). While listed as separate domain, affect has an interdependent relationship with cognition and learning. Specifically, confusion, frustration, boredom, surprise, delight, flow, and anxiety are considered major moderators of learning (D'Mello 2013; Pekrun 2006). For example, cognitive readiness—the capability to maintain performance and mental well-being in complex, dynamic, unpredictable environments that may elicit affective responses. Dimensions of cognitive readiness, according to Kluge and Burkolter (2013), include concepts such as risk-taking behavior, emotional stability and coping, which may be considered part of the affective domain.

A revision of Bloom's Taxonomy (Anderson and Krathwohl 2001) tracks a series of behaviors from low-affective state to high: 1) **receiving** – the learner takes in information, 2) **responding** – the learner takes in information and responds/reacts, 3) **valuing** – the learner attaches value to information, 4) **organizing** – the learner sorts information and builds mental models, and 5) **characterizing –** the learner matches mental models to values and beliefs ultimately influencing (e.g., promoting or limiting) the learner's behavior.

Very little training (outside of classroom-based training) is currently provided to exercise/grow skills in this important task domain and almost no adaptive training has been created to support this domain. However, D'Mello and Graesser (2012) have produced an affect-sensitive tutor that exercises emotional intelligence using the AutoTutor authoring tools. Research is needed to understand measures for the affective task domain and any unique characteristics required to author affective domain scenarios.

## 5.3 Psychomotor Domain

Sometimes called the "doing" or "action" domain, tasks in this domain are associated with physical tasks (e.g., marksmanship) or manipulation of a tangible interface (e.g., remotely piloting a vehicle), which may include physical movement, coordination, and the use of the motor-skills. Development of motor-skills requires practice and is measured in terms of speed, precision, distance, procedures, or techniques during execution (Simpson 1972). Simpson's hierarchy of psychomotor learning ranges from low to high: 1) **perception** – the ability to use sensory cues to guide motor activity; 2) **set or readiness to act**; 3) **response** –

early stages of learning a complex skill through imitation and trial and error; 4) **mechanism** –habitual learned responses; 5) **complex overt response** – skillful performance of complex movements; 6) **adaptation** – well-developed skills that are modified to support special requirements; and 7) **origination** – the development of new movement patterns to fit unique situations.

While this domain is well represented in US Army training, research is needed to build adaptiveness into these training systems and thereby optimize deep learning. Again, a goal of this research is to reduce the time to competency to allow time for automaticity through overtraining and deeper learning experiences that transfer to the operational environment.

## 5.4 Social Domain

Sometimes called the "collaborative" domain, tasks in this domain include a set of collaborative characteristics or measures of learning in the social domain as defined by Soller (2001): 1) **participation**, 2) **social grounding** – team members "take turns questioning, clarifying and rewording their peers' comments to ensure their own understanding of the team's interpretation of the problem and the proposed solutions", 3) **active learning conversation skills** – quality communication, 4**) performance analysis and group processing** – groups discuss their progress, and decide what behaviors to continue or change (Johnson et al. 1990) and 5) **promotive interaction** – also known as "win-win" this characteristic occurs when members of a group perceive that they can only attain their goals if their team members also attain their goals.

This domain is different from the cognitive, affective, and psychomotor domain in that Soller's collaborative learning skills taxonomy is multilayered: skills, subskills, and attributes/behaviors as shown below:

- Conversation Skill
  - Task subskill: Coordinate group process, request focus change, summarize information, and end participation behavior
  - Maintenance subskill: Request attention, suggest action, request confirmation, listening behavior, and apologize behaviors
  - Acknowledge subskill: Appreciation, accept/confirm, and reject behaviors

- Active Learning Skill
  - Request subskill: Information-seeking, elaboration, clarification, justification, opinion-seeking, and illustration behaviors

- Inform subskill: Rephrase, lead, suggest, elaborate, explain/clarify, justify, and assert behaviors
- Motivate subskill: Encourage and reinforce behaviors

- Creative Conflict Skill
  - Argue subskill: Conciliate, agree, disagree, offer alternatives, infer, suppose, propose exception, and doubt behaviors
  - Mediate subskill: Teacher mediation

The Program for International Student Assessment (PISA) (2015) is a worldwide study by the Organization for Economic Cooperation and Development (OECD) in both member and nonmember nations. This study focuses on 15-year-old students and their scholastic performance in mathematics, science, and reading. During PISA 2015, OECD defined a matrix of collaborative problem-solving skills (Table 1). Some of the skills and associated behaviors in this matrix may also apply to situational problem solving in the US Army (e.g., staff-level organizations evaluating options to meet objectives during military operations). Research is needed to determine if the model in this matrix will generalize beyond its original application to 15-year-old students.

**Table 1       Matrix of collaborative problem solving skills**

| | (1) Establishing and maintaining shared understanding | (2) Taking appropriate action to solve the problem | (3) Establishing and maintaining team organisation |
|---|---|---|---|
| (A) Exploring and Understanding | (A1) Discovering perspectives and abilities of team members | (A2) Discovering the type of collaborative interaction to solve the problem, along with goals | (A3) Understanding roles to solve problem |
| (B) Representing and Formulating | (B1) Building a shared representation and negotiating the meaning of the problem (common ground) | (B2) Identifying and describing tasks to be completed | (B3) Describe roles and team organisation (communication protocol/rules of engagement) |
| (C) Planning and Executing | (C1) Communicating with team members about the actions to be/ being performed | (C2) Enacting plans | (C3) Following rules of engagement, (e.g., prompting other team members to perform their tasks.) |
| (D) Monitoring and Reflecting | (D1) Monitoring and repairing the shared understanding | (D2) Monitoring results of actions and evaluating success in solving the problem | (D3) Monitoring, providing feedback and adapting the team organisation and roles |

Research is needed to create and apply measures for both collaborative learning and team training activities. The interdependent nature of US Army tasks also requires tutoring of squads and other echelons of teams (collective training).

Research is also needed to develop team state models to drive adaptive training decisions. An extensive review of the team performance and tutoring literature has been conducted (Burke et al. 2015, in press) to determine antecedents of team outcomes (i.e., performance, learning, satisfaction, and viability), which include behavioral measures (Table 2), along with models of cooperation (Table 3), and team cognition (Table 4).

**Table 2      Team states and behavioral measures**

| | Team Performance | Team Learning | Team Satisfaction | Team Viability |
|---|---|---|---|---|
| **Team Behaviors** | | | | |
| Communication | YES | YES | YES | YES |
| Coordination | YES | YES | YES | YES |
| Mutual Support | YES | NOT EXAMINED | YES | TENTATIVE |
| Reflexivity | YES | YES | YES | NOT EXAMINED |
| Monitoring | YES | NOT EXAMINED | NOT EXAMINED | NOT EXAMINED |
| Conflict | YES | TENTATIVE | YES | YES |
| Task | YES | NOT EXAMINED | YES | YES |
| Relationship | YES | NOT EXAMINED | YES | YES |
| Transaction | YES | TENTATIVE | TENTATIVE | NOT EXAMINED |
| Action | YES | TENTATIVE | TENTATIVE | NOT EXAMINED |
| Interpersonal | YES | TENTATIVE | NOT EXAMINED | NOT EXAMINED |
| Leadership | YES | NOT EXAMINED | YES | NOT EXAMINED |
| Organizational Citizenship Behaviors | YES | NOT EXAMINED | NOT EXAMINED | NOT EXAMINED |
| Conflict Management | YES | TENTATIVE | YES | TENTATIVE |

**Table 3     Team states and measures of cooperation**

| | Team Performance | Team Learning | Team Satisfaction | Team Viability |
|---|---|---|---|---|
| **Cooperation** | | | | |
| Trust | YES | YES | YES | NOT EXAMINED |
| Collective Efficacy | YES | NOT EXAMINED | YES | YES |
| Psychological Safety | YES | TENTATIVE | TENTATIVE | TENTATIVE |
| Cohesion | YES | TENTATIVE | YES | TENTATIVE |
| Justice | TENTATIVE | NOT EXAMINED | NOT EXAMINED | NOT EXAMINED |

**Table 4     Team states and team cognition measures**

| | Team Performance | Team Learning | Team Satisfaction | Team Viability |
|---|---|---|---|---|
| **Team Cognition** | | | | |
| Team Mental Models | YES | NOT EXAMINED | YES | NOT EXAMINED |
| Transactive Memory Systems | YES | NOT EXAMINED | TENTATIVE | YES |
| Situation Awareness | YES | NOT EXAMINED | NOT EXAMINED | NOT EXAMINED |

Blocks in each table indicate either: "YES" to represent a significant effect was found between 1 of the antecedents examined in the literature review and 1 of the team outcomes; "TENTATIVE" to represent some effect or conflicting evidence was found between 1 of the antecedents examined and 1 of the team outcomes; or "NOT EXAMINED" to represent that these relationships were not examined as part of this literature review and meta-analysis. The "NOT EXAMINED" category represents a set of opportunities for future research in team tutoring.

Additional discussion of research in the social domain may be found on team cognition (Salas and Fiore 2004), team mental models (Fletcher and Sottilare 2013; Rouse et al. 1992), and situational awareness in team performance (Salas et al. 1995).

## 6.    Domain Modeling Research Goals and Challenges

A foundational goal of adaptive training research at ARL is to model the perception, judgment, and behaviors of expert human tutors to support practical, effective, and affordable learning experiences guided by computer-based agents. To this end, 5 primary goals for domain modeling for adaptive training systems

have been identified and are discussed in this section along with the major challenges or barriers to success.

## 6.1 Representing and Understanding the Influence of Domain Attributes

Our first goal is to conduct research to determine the influence of task domain attributes (e.g., complexity, definition, and dynamics) on cognitive mechanisms (e.g., learning, comprehension, performance, retention, reasoning, and transfer of knowledge and acquired skills to the operational environment). Research is needed to analyze related and unrelated domains to determine commonalities, performance measures, and user requirements.

The challenge in meeting this goal is that since each domain contains unique domain knowledge, the relationship of these attributes to the cognitive mechanisms listed previously are not well understood across various task domains (cognitive, affective, psychomotor, social, and hybrid tasks). It may be possible to generalize relationships in a particular task domain with the goal being to identify attributes with high effect on cognitive mechanisms.

Also important to this research goal is the ability to define how these attributes are measured, how qualitative inputs are going to be assessed against quantitative metrics, and how stakeholder requirements and learner-generated content (e.g., social media input on relevance and impact) influences the modeling of each domain. There needs to be a matching between the desired requirements and what is actually authored in the domain. For example, tutors for marksmanship for the US Army and Marines may be very similar based on the task domain (psychomotor) but may also have different instructional methods or concepts based on organizational requirements.

## 6.2 Reducing Time, Cost, and Skill to Author and Deliver Instruction

Our second goal is to discover and improve authoring tools and methods to more easily represent domain knowledge including methods to select optimal instructional tactics (actions) based on sound instructional strategies (plans), the instructional context, and the learner's states and traits (Murray 1999; Murray 2003; Sottilare and Gilbert 2011; Murray 2015). Specifically, our goal is to provide sufficient domain knowledge to effectively adapt the training of the task for individual learners and units while significantly lowering the cost and skills needed to author adaptive training systems for the US Army.

Authoring in complex domains is a time intensive process and research is needed to determine what attributes of the domain model influence successful outcomes (e.g., skill development) and antecedents to those outcomes (e.g., motivation, engagement, and grit), which may influence the complexity, definition, and dynamics of the domain knowledge (e.g., content, feedback, and assessments) presented to the learner and thereby influence the cost.

Adaptive training systems by their nature offer more flexibility and are tailored to individual learners. Given the variability of learner attributes across the general population, this creates a greater demand for domain authoring. Finding efficient methods to create new content and to reuse existing content (e.g., training content in existing US Army training simulations) should be a priority for domain modeling research. Specifically, we need to examine methods to automate large portions of the authoring process including the automated development of expert models (sometimes called ideal student models), the automated generation of scenario variants from base cases, and the authoring of assessments from which the ITS determines progress and corresponding strategies and tactics.

Additionally, our goal is to discover/improve methods to provide adaptive instruction that is easily accessible and is available at the Soldier's point-of-need (anyplace) and anytime (24/7/365).

## 6.3 Improving the Interoperability of Domain Models

Our third goal is to develop standards for interoperability to promote reuse of domain knowledge (e.g., content, expert models, question banks, assessments, and tactics). Specifically, our goal is to set interoperability standards for US Army training resulting in reduced development and maintenance costs and increased speed of adoption for adaptive training technologies. The major challenges are that no standards exist for adaptive training and interoperability—the ability to pull and replace one model or domain element with another authored elsewhere— is extremely low. Effort should be expended to work with the ITS community to develop interoperability standards to maximize reuse of domain knowledge. Defining standard methods of representing and interfacing with domain knowledge will allow a single adaptive training architecture or framework to support multiple domains and reduce authoring costs. This is the primary driver for the development of GIFT.

The US Army's focus on scenario-based training along with the significant investment in training infrastructure should also be considered in developing interoperability. To this end, GIFT includes a standard interface specification, or gateway, so that US Army training systems that meet this specification can be

integrated to provide adaptive training capabilities. In addition, the GIFT gateway currently has an Institute of Electrical and Electronics Engineers (IEEE) 1278 Distributed Interactive Simulation (DIS) compliant interface to receive tactical data (e.g., entity location) to support instructional decisions and to push instructional tactics (e.g., interaction with the learner or changes to the training environment) to DIS-compatible training simulations.

## 6.4 Optimizing the Selection of Tactics

Our fourth goal is to optimize the selection of tactics—domain-specific actions by the tutor—to provide the greatest opportunity for performance, learning, retention, and transfer. In GIFT, tactics are the actions taken by the tutor in response to learner states and instructional context (e.g., conditions of the scenario or problem presented), as shown in Fig. 2 and are constrained by available options provided during the authoring process. Improving the usability and efficiency of authoring tools will likely result in a greater number of available options for adaptive training domains.
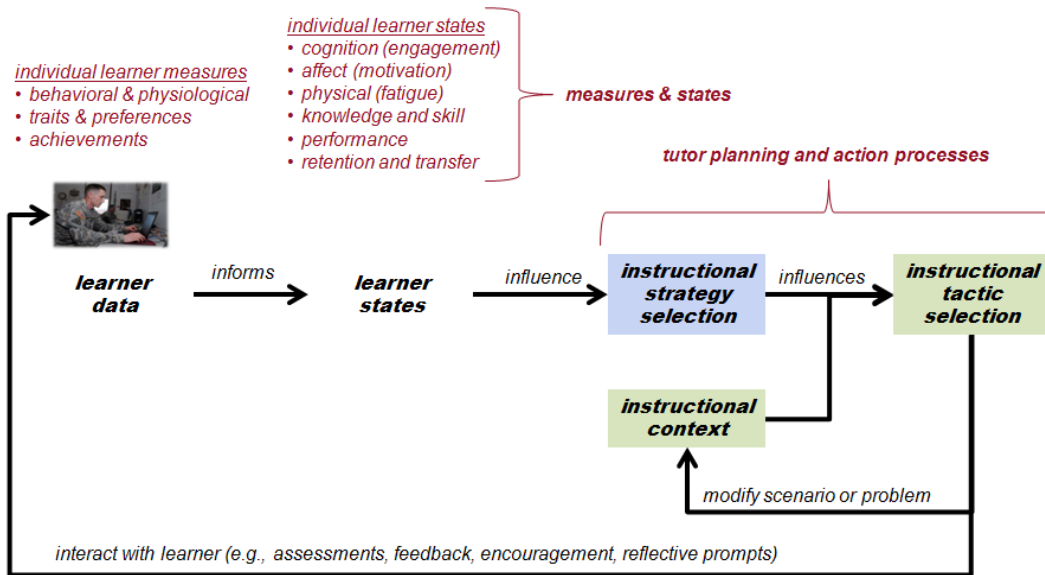


**Fig. 2     Updated individual learning effect model**

Unlike instructional strategies, which are derived from good pedagogical practices based on learning theory and influenced by the learner's states, tactics are domain-specific actions by the tutor and may not be generalized across all task domains. Research is needed to determine methods to select the best possible tactic given the selected instructional strategy, the training domain, and the availability of tactics.

Modeling the expert behaviors of human tutors may be a starting point, but accurate assessment methods are needed for both individual and team-level states. These states are critical in selecting appropriate strategies (plans for action) and tactics (actions: e.g., assessments, feedback, questions, changes to the training environment) per the Learning Effect Model (Sottilare 2012; Fletcher and Sottilare 2013; Sottilare 2013; Sottilare et al. 2013b) as updated for both individuals (Fig. 2) and teams (Fig. 3). Assessment of team states may also be useful in determining constraints to be monitored by tutoring agents and interactions with the learner and the training environment as shown earlier in Fig. 1.
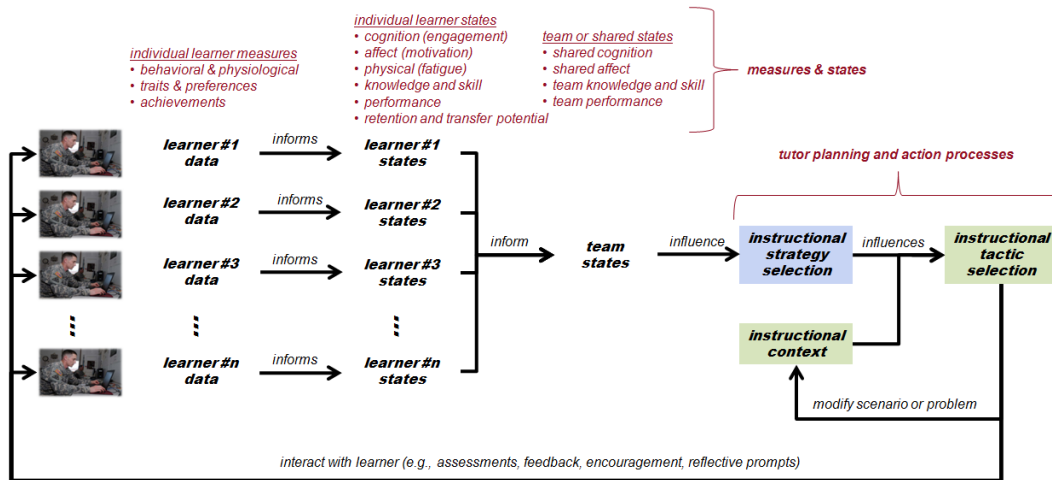


**Fig. 3    Updated team learning effect model**

## 6.5  Extending Adaptive Training to Militarily Relevant Domains

Our fifth goal is to be able to extend adaptive training to support militarily relevant domains. Many military tasks are hybrids of task domains in that they include aspects of cognitive (thinking: evaluating, problem-solving, and decision-making), affective (feeling: making value judgments), psychomotor (doing: physical action), and/or social (collaborating: working in teams). US Army training differs greatly from traditional ITS's, which are primarily problem-based (e.g., mathematics, physics, computer programming) and generally vary only in complexity. Given much of US Army training is scenario-based, the **realism** of the training environment, **accessibility** of the training, the **complexity** of the scenario, the **physical dynamics** of the task, and the variable level of **definition** are all design considerations for adaptive training systems for military use. It will be essential to match the attributes of the environment to the task domain by asking the question, "What is necessary to train the task effectively?" This variability in adaptive training and educational domains will allow for greater

opportunities for Soldiers to train at the point-of-need and to train more closely to how they fight. This is anticipated to result in greater learning, performance, retention, and transfer of skills to the operational environment.

As in all training, it will be essential to match the realism of the training environment (e.g., serious game, virtual simulation, embedded training) to enable learners to progress toward established learning objectives. For embedded training where Soldiers bring training with them in their operational platform (e.g., ground, air, sea, dismounted), considerations should be made regarding the visual resolution of virtual elements of the training environment and what is required to train the task (Sottilare et al. 2007). For example, if the resolution of virtual targets is insufficient to support either detection or identification of the targets at comparable distances to the real world (also known as live environment), then negative training may result.

Another consideration in militarily relevant domains is accessibility. Accessible learning is being directly addressed by the research and development of GIFT (Sottilare et al. 2012a, 2012b; Sottilare et al. 2013a), an adaptive tutoring architecture that is modular and service-oriented. GIFT will also support access to adaptive tutoring resources (e.g., domain content, assessments, Web services) via the Internet and allow content to be presented in a Web browser.

Adaptive training solutions must be able to include the complexities of each to provide tailored training across the broad spectrum of Soldier tasks. This includes the ability to align more closely with the nature of those tasks to promote transfer of skills from training systems to the theaters of operation. Ultimately, this will mean moving from desktop training environments to more interactive and physical environments. Research will be needed to examine a learning progression from the desktop to the wild, a concept where Soldiers can receive training anywhere. We examine 4 modes of adaptive training environments to support this concept.

Variable task dynamics refer to the physical modes of interaction of the learner during the training experience. This ranges from static (seated position for desktop training), to limited dynamic (standing position limited range of mobility in instrumented areas), to enhanced dynamic (standing, kneeling, and prone positions with expanded mobility in instrumented areas), to "in-the-wild" (any position with unlimited mobility where sensors and communications move with the Soldier).

Variable task definition refers to how well the domains are understood in terms of standards and measures-of-performance. Well-defined domains (e.g., mathematics) typically have 1 correct path to a successful outcome and a set of

specific standards for measuring success. Ill-defined domains may have multiple paths to successful outcomes, and they tend to have vague standards and less defined measures of success. Ill-defined domains may also have unexpected and inconsistent confounds that could cause learning to be perceived when there really is a mediating underlying factor. Analyzing these can provide greater knowledge to answering the "why" behind performance and learning outcomes.

Finally, task complexity refers to the range of difficulty in understanding and performing the task. Task complexity can range from simple procedural tasks to more complex multidimensional tasks.

Next, we examine modes of dynamic interaction. Limited dynamic environments support hybrid (i.e., cognitive, affective, psychomotor) tasks where a larger degree of interaction with the environment and other learners is critical to learning, retention, and transfer to the operational environment. Decision-making and problem-solving tasks may be taught easily in a limited dynamic mode along with tasks requiring physical orientation (e.g., land navigation).

Enhanced dynamic environments support tasks where freedom of movement and a high degree of interaction with other learners are critical to learning, retention, and transfer to the operational environment. Building clearing and other team-based tasks may be taught easily in an enhanced dynamic mode.

"In-the-wild" mode is transferring tutoring to the operational environments and could also be called embedded training for Soldiers. In-the-wild mode is critical to support tasks where a very high degree freedom of movement and a high degree of interaction with other learners are critical to learning, retention, and transfer to the operational environment. It is anticipated that psychomotor and social tasks may be best taught in-the-wild or an environment more closely resembling the operational environment.

## 7.  Interdependencies with Other Adaptive Training Research Vectors

This section examines interdependencies between domain modeling and the other 5 adaptive training research vectors (Fig. 4). This discussion forms the basis for the sequencing of research and ultimately bringing adaptive training capabilities into a state of practice.
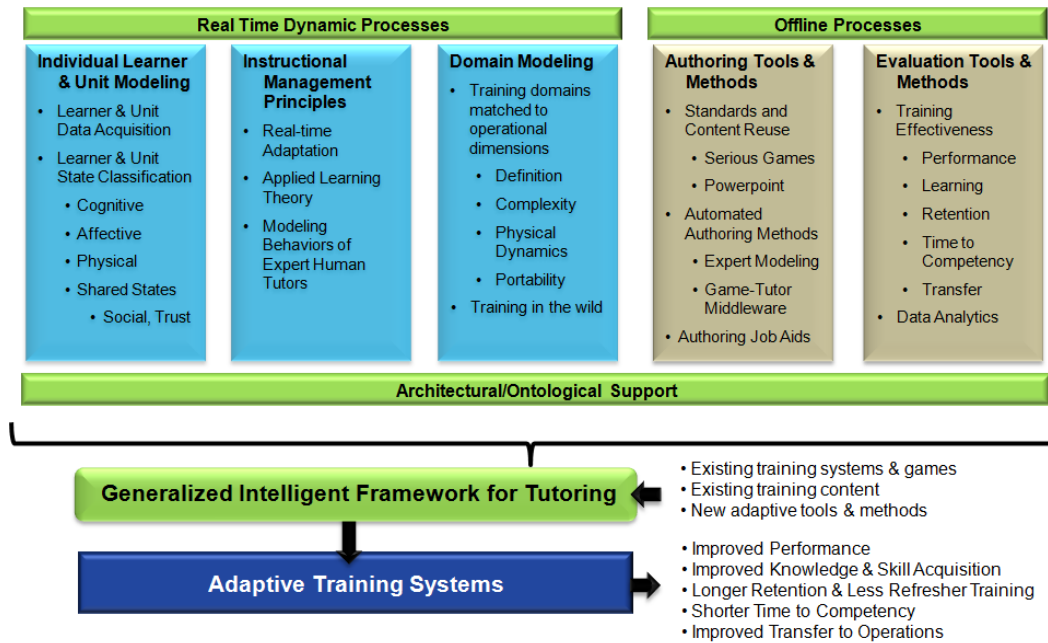
**Fig. 4    Adaptive training research vectors**

Accurate methods to classify individual and team learner states are a necessary precursor to selecting optimal instructional strategies as noted in the learning effect models for individual learners (Fig. 2) and teams of learners (Fig. 3). In turn, instructional strategies along with instructional context are necessary precursors to selecting optimal instructional tactics and ultimately significant effect on desired outcomes: learning, performance, retention, and transfer.

## 7.1  Learner Modeling and Domain Modeling

Adaptive training systems are learner-centric systems. Independent of the domain under training, accurate modeling of the learner is critical to driving instructional decisions in adaptive training systems. However, collection and maintenance of this data may be costly; therefore, it is necessary to select measures and states that significantly impact our desired outcomes: learning, performance, retention, and transfer. Research is needed to determine what this dataset will look like. Candidates abound in the literature, but in general these include transient data/states, cumulative states (building over time), and enduring data/states (Paneva 2006). It should be noted that learning falls into both transient and cumulative states. It is necessary to understand progress toward domain competency in addition to measures of near-term performance. It is important to understand how domain-specific learning (skills) decay over time.

Transient measures of importance include individual behavioral and physiological data, and cognitive, affective, physical, and social states to represent learning.

Cumulative measures include achievements (e.g., certifications, training, education, and experiences), affiliations, work history, and domain competency. More enduring information about the learner might include: gender, culture, first language, physical constraints (e.g., colorblind/deaf), values, personality attributes, or other trait-based information (Sottilare and Brawner 2014). All of these measures/states are potential drivers for adaptive training decisions.

## 7.2 Automated Instruction and Domain Modeling

In GIFT, instructional management takes place in 2 modules/processes within the learning-effect model. One process is instructional strategy selection within the pedagogical module. The second is within the domain module where specific tactics or actions are selected based on the strategy selection and instructional context. Standard representation of tactics and other domain knowledge components are needed to support interoperability, modularity, and reuse of instructional elements to reduce the cost of authoring and maintaining adaptive training systems.

## 7.3 Authoring Tools and Methods

Authoring tools and methods are needed to search, retrieve, curate, and apply domain knowledge to adaptive training systems. Automation of these processes is needed to reduce the overhead of gathering and organizing domain knowledge and authoring adaptive training systems. Two developing automation capabilities include tools to rapidly develop expert models through data mining of text-based material (e.g., field manuals), and automated generation of child scenarios from parent scenarios. Development of new user interfaces for authors is needed to make authoring of domain knowledge easier for authors who are domain experts, but lack computer science and instructional system design skills. Finally, adaptive training systems require capabilities to interpret user-generated content (e.g., social media) to support domain-specific changes (e.g., improved accuracy tactics selection algorithms, alternate domain content) to ensure the learner population is engaged in the training process.

## 7.4 Evaluation

Research is needed to evaluate and optimize the effect of tactics selected within the GIFT domain module upon desired outcomes: learning, performance, retention, and transfer. To understand the impact of domain-specific instructional decisions, research is needed to provide stealth assessment of learners (Shute et al.

2013). Long-term effects (deep learning, retention, and transfer) are also important in evaluating the impact of adaptive training methods.

## 7.5 Architecture

GIFT, as the architecture to facilitate adaptive training, will need to support the acquisition and interpretation of data required by the domain module to support optimal instructional tactics selection per the learning effect models (Figs. 3 and 4).

## 8.  Conclusions

This report outlines the ARL's plans for conducting research in adaptive training and education to support the US Army Learning Model. Specifically, this report relates to domain modeling and the answer to the question: What adaptive training methods provide the best value (in terms of effectiveness and affordability) for the comprehensive modeling of US Army Training and Education Domains?

This report outlined goals to:

- model and understand the efforts required to author domains of varying complexity, definition, and physical dynamics;

- support authoring of ill-defined and well-defined task domains;

- support authoring of militarily relevant training and education domains across the spectrum of cognitive, affective, psychomotor, and social tasks;

- match the nature of military tasks to training environments and optimize transfer to operational environments;

- accurately assess learning and domain task performance in real-time;

- promote optimal learning, performance, retention and transfer (on-the-job performance) across domains;

- support individual and team training (e.g., small unit and collective training) and education (e.g., collaborative learning and problem-solving) experiences.

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## List of Symbols, Abbreviations, and Acronyms

| | |
|---|---|
| σ | sigma |
| AAR | after-action review |
| AI | artificial intelligence |
| ALM | US Army Learning Model |
| ARL | US Army Research Laboratory |
| DIS | Distributed Interactive Simulation |
| FHTE-LS | Future Holistic Training Environment for Live and Synthetic |
| GIFT | Generalized Intelligent Framework for Tutoring |
| h | hour(s) |
| IEEE | Institute of Electrical and Electronics Engineers |
| ITS | intelligent tutoring system |
| MOS | military occupational specialty |
| OECD | Organization for Economic Cooperation and Development |
| PISA | Program for International Student Assessment |
| SRL | self-regulated learning |
| S&T | Science and Technology |
| STE | Synthetic Training Environment |
| T&E | training and education |
| UTM | Unit Training Management |
| WFO | Warfighter Outcome |

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