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Adaptive Intelligent Tutoring System (ITS) Research in Support of the Army Learning Model—Research Outline

by Robert A. Sottilare

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14. ABSTRACT

Current Army standards for training and education are *group instruction* and *classroom training* also known as one-to-many instruction. Recently, the Army has placed significant emphasis on self-regulated learning (SRL) methods to augment institutional training. Per the Army Learning Model (ALM), Soldiers will be largely responsible for their own learning. One-to-one human tutoring has been shown to be significantly more effective than one-to-many instruction, but is not practical. An alternative to one-to-one human tutoring is one-to-one computer-based tutoring using Intelligent Tutoring Systems (ITSs), which have been shown to be effective in promoting individual learning in static, simple, well-defined domains (e.g., mathematics). To be practical, high authoring costs and limited adaptiveness barriers must be addressed. This outline describes a strategy to address key ITS design challenges and expand the horizons of SRL. Research is needed to: reduce cost/skill to author ITSs; enhance the adaptiveness of ITSs; and expand ITSs domains to support more dynamic, complex, and ill-defined domains to match the Army's operational mission. The interdependent nature of Army tasks also requires tutoring of squads and other teams. The intent of this report is to inform and educate stakeholders, and focus potential collaborators on relevant issues within the adaptive tutoring research space.

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1. Background

The current Army standards for training and education are group instruction and classroom training also known as one-to-many instructional methods. Classroom training has been generally focused on acquiring knowledge and applying knowledge in proxies for live training environments (e.g., desktop virtual simulations, serious games). Small group instruction in live environments has also been used to assess application of knowledge and development of skills. A standard feedback mechanism for Army training is the after-action review (AAR) where significant decision points and actions are captured for small group discussion conducted after the completion of a training event.

Recently, the Army has placed significant emphasis on self-regulated learning methods to augment institutional training. Under the Army Learning Model (ALM) concept (U.S. Army Training and Doctrine Command, 2011), Soldiers will be largely responsible for their own learning, but will clearly still need personal guidance or tutoring to be effective. One-to-one human tutoring has been shown to be significantly more effective than one-to-many instructional methods (e.g., classroom instruction: Bloom, 1984; VanLehn, 2011), but it is not practical or affordable to have one human tutor for each Soldier in the Army.

A practical alternative to one-to-one human tutoring is one-to-one computer-based tutoring methods such as Intelligent Tutoring Systems (ITSs). Figure 1 compares the effect sizes of various tutoring methods. ITS methods vary from 0.80 to 1.05 σ as compared to tradition classroom training (0.00 σ). These are promising results and equate to an increase of a letter grade or more improvement over other methods.

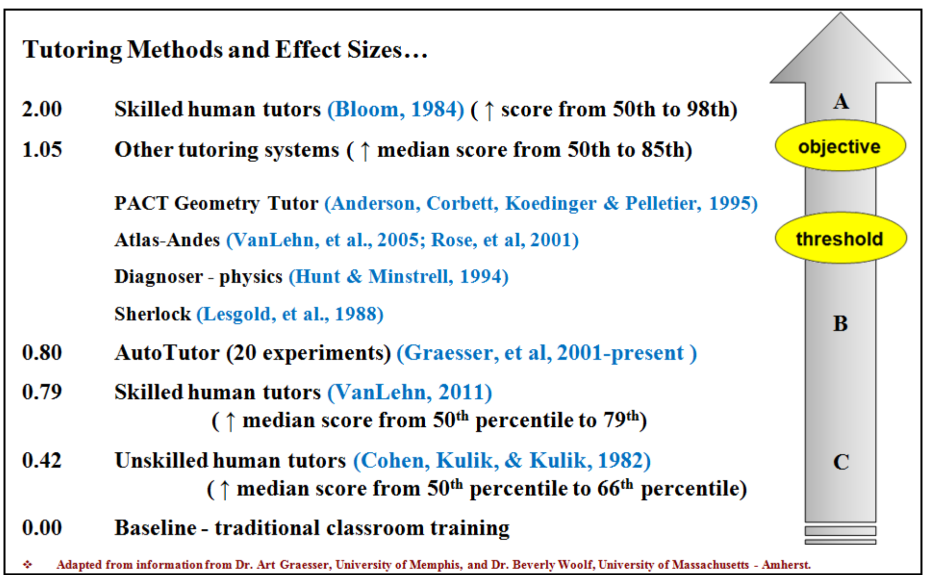

Figure 1. Effectiveness of various tutoring methods.

ITSs have been shown to be effective in promoting learning in static, relatively simple, well-defined domains (e.g., mathematics, physics) for individual learners. For our purposes, static domains are desktop learning tools where the movement of the Soldier is restricted to activities conducted while seated. Static domains can effectively support tasks involving knowledge acquisition and decision making but are currently less useful for training tasks involving learner motion (e.g., psychomotor learning) and perception.

While ITSs technologies are promising, ITSs are expensive to author and are insufficiently adaptive to support tailored, self-regulated training experiences across a broad spectrum of military tasks as required by the ALM. In order for ITSs to be practical on a large scale, barriers to adoption such as expense and limited adaptiveness must be addressed. Adaptive tutors must automatically adjust the challenge and level of support to meet each Soldier's learning needs in real time. To accomplish this, adaptive tutors, like their human counter-parts, must be able to:

- acquire learner data (e.g., behaviors),
- use learner data to determine the learner's state (e.g., confusion), and
- select an optimal instructional strategy (e.g., metacognitive prompt) to address the learner's state resulting learning gains (e.g., knowledge acquisition).

This sequence of events is known as the adaptive tutoring learning effect chain (Sottilare, 2012; Sottilare et al., 2013) and is shown in figure 2.

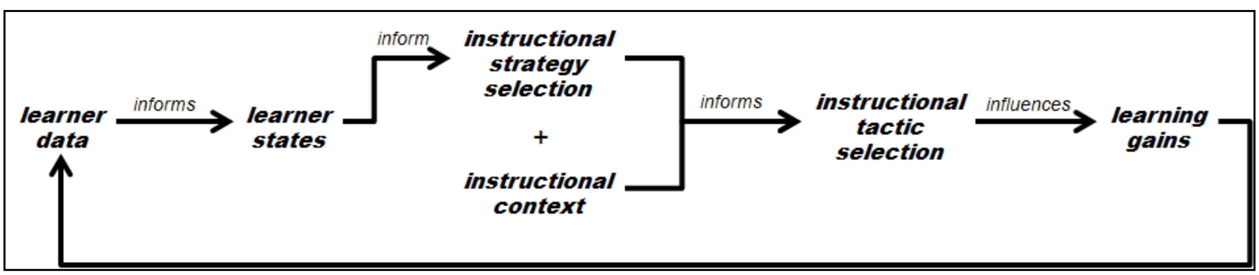

Figure 2. Adaptive tutoring learning effect chain.

Research is also needed to support broad accessibility; develop tools to reduce cost and skill needed to author ITSs; enhance the perception of ITSs; improve the adaptiveness of instruction to meet individual learner needs; and expand ITS domains to support more dynamic, complex, and ill-defined tutoring of tasks that match the Army's operational mission. The interdependent nature of Army tasks also requires modeling of and feedback for teams of Soldiers as well as individuals.

This research outline describes a focused strategy to address key adaptive tutoring design challenges and expand the horizons of self-regulated learning. The strategy identifies Army Science and Technology (S&T) requirements for new capabilities, research goals for adaptive tutoring, research vectors to discover new methods and innovate existing methods, and transition mechanisms.

2. Army S&T Requirements for Adaptive Intelligent Tutoring Systems

The Army S&T 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 Tutoring Research program is targeting elements of five WFOs.

2.1 Integrated Training Environment (WFO T1)

A portion of ARL's adaptive tutoring research is aiming to support interaction between ITSs and elements of the existing Army training infrastructure to provide an integrated training environment (ITE). Goals include compatibility and interoperability with Army serious games and simulations to support engaging and effective learning experiences.

2.2 Accessible Learning Capability (WFO T2)

Accessible learning is being directly addressed by the research and development of Generalized Intelligent Framework for Tutoring (GIFT) (Sottilare et al., 2013), an adaptive tutoring architecture that is modular and service-oriented. GIFT will also support access to adaptive tutoring resources (domain content, assessments, Web services) via the Internet and allow content to be presented in a Web browser.

2.3 Enhanced Gaming Capability (WFO T4)

The integration of adaptive tutoring capabilities with engaging serious game capabilities will enable more effective training. Automating the integration games and tutors is a goal of the adaptive tutoring research program. This will reduce the cost, time, and skill needed to integrate Army training games and ITS.

2.4 Individual Training for Tactical Tasks (WFO T5)

The evolving adaptive tutoring architecture, GIFT, is being evaluated across a broad variety of tasks that include individual tactical tasks. Future capabilities will enable individual and small unit tasks across cognitive, affective, psychomotor, and social domains. Research to examine how tutoring approaches vary based on the dynamics, definition, and complexity of tasks is ongoing and described in Section 4. Research Vectors, 4.3 Domain Modeling, later in this report. This research will enable guided learning across a broad spectrum of Soldier tasks that are not possible with today's ITS or training simulation technology alone.

2.5 Adaptive Training and Innovative Learning (WFO T8)

This last WFO is being directly addressed through adaptive tutoring research and the development of GIFT, which will support a testbed capability to evaluate various adaptive tutoring technologies in a variety of training domains. This research will provide empirical evidence to guide ITS design decisions and develop standards of performance captured within GIFT to support reuse and may be used to develop effectiveness in the future.

3. Research Goals

The foundational goal of adaptive tutoring research at the U.S. Army Research Laboratory (ARL) is to *model the perception and behaviors of expert human tutors* to support practical, effective, and affordable learning experiences guided by computer-based agents. Ten goals have been identified for the adaptive tutoring research program to conduct research to:

1. *Significantly lower the cost and skills needed to author* effective adaptive tutoring systems for the U.S. Army.
2. Make ITS *easily accessible and available* at the Soldier's point-of-need.
3. Enable ITS to autonomously perceive the learner's state and adapt (tailor) instruction to meet each Soldier's individual learning needs.
4. Enhance Soldier engagement to promote more efficient and effective learning and retention.
5. Accelerate learning to reduce each Soldier's time-in-training while retaining the same level of learning and retention.
6. Discover adaptive tutoring methods to support team tutoring and collaborative learning to match unit-level training needs so teams of Soldiers can *train as they fight*.
7. Discover, innovate, leverage, and transition adaptive tutoring technologies (tools and methods) resulting in enhanced learning and retention capabilities and higher levels of reuse for training and education.
8. Blur the lines between tutoring and training technologies to support more effective guided learning experiences, which reuse the engaging content of simulation with the automated tailored pedagogy of ITS (e.g., game-based tutoring) to produce Soldiers who persevere, adapt, collaborate, and think critically.
9. Support the unique U.S. Army training scope in domains of higher complexity, higher dynamics, and lower definition for both individuals and teams of Soldiers so they can *train as they fight*.

10. Conduct Soldier evaluations of adaptive tutoring technologies (tools and methods) to determine their learning effect and establish best practices.

A set of longer range objectives are tied directly to the salient characteristics of a vision for adaptive tutoring termed *platinum tutors*. The characteristics of platinum tutors, as opposed to the characteristics of ITS of lower capabilities (e.g., bronze, silver and gold tutors), were derived from Sottilare and Gilbert's (2011) initial description of tutoring capability levels. Elements of this list align closely with the INSPIRE (intelligent, nurturant, Socratic, progressive, indirect, reflective and encouraging) model of tutoring described by Lepper and Woolverton (2002). The revised list of *platinum* characteristics is presented in the following:

- *Adaptive*—refers to the use of artificial intelligence techniques to perceive and make optimal decisions to tailor instruction in real time to meet the self-regulated and blended learning needs of individual Soldiers and team of Soldiers. Adaptive systems are able to customize themselves in response to changes in the learner and/or the training environment.
- *Credible*—instills trust in the learner through demonstrated expertise in the domain being tutored; always provides valid information; more effective than an expert human tutor in one-to-one and one-to-many training/tutoring environments.
- *Personal and communicative*—instills trust in the learner through positive personal communication that encourages learner-initiated dialog and question asking leading to higher learner performance.
- *Relevant*—able to support military training across a broad spectrum of operational tasks ranging from ill-defined domains to well-defined domains, from simple procedures to multidimensional complex activities, and from relatively static interaction to highly dynamic interaction.
- *Accurate and valid*—nearly 100% accurate or at least more accurate than an expert human tutor in assessing the state(s) of the learner; uses optimal instructional methods based on the current/projected state of the learner; instructional methods are derived through rigorous experimentation.
- *Usable*—tailored tools, methods, and interfaces to support different types of users (e.g., learners, trainers/instructors, training and tutoring system developers, instructional system designers) by structuring their knowledge for easy retrieval.
- *Accessible*—service-oriented, available anywhere 24/7/365 to support Soldier learning at the point of need.
- *Affordable*—time to author is reduced from years/months to days/hours; noncomputer scientists can easily author; promotes standards and reuse to lower development cost.

- *Persistent*—models the learning capabilities and needs of Soldiers across their careers; instills trust in the learner by accurately modeling and anticipating the needs of the learner.

4. Research Vectors

To support the goals previously identified, the adaptive tutoring research team has organized their research around five vectors as shown in figure 3. The first three vectors (blue boxes) focus on the knowledge and methods needed to support the adaptive tutoring real-time process and are specifically tied to the adaptive tutoring learning effect chain. The last two vectors (gray boxes) focus on offline (non-real-time) processes to support authoring and analysis goals. Together the five vectors described in the following subsections will enable the development of GIFT, a modular, service-oriented, agent-based tutoring architecture to support standards, reuse, and best practices for adaptive tutoring. Additional information about GIFT is available at https://www.gifttutoring.org/projects/gift/wiki/Overview.

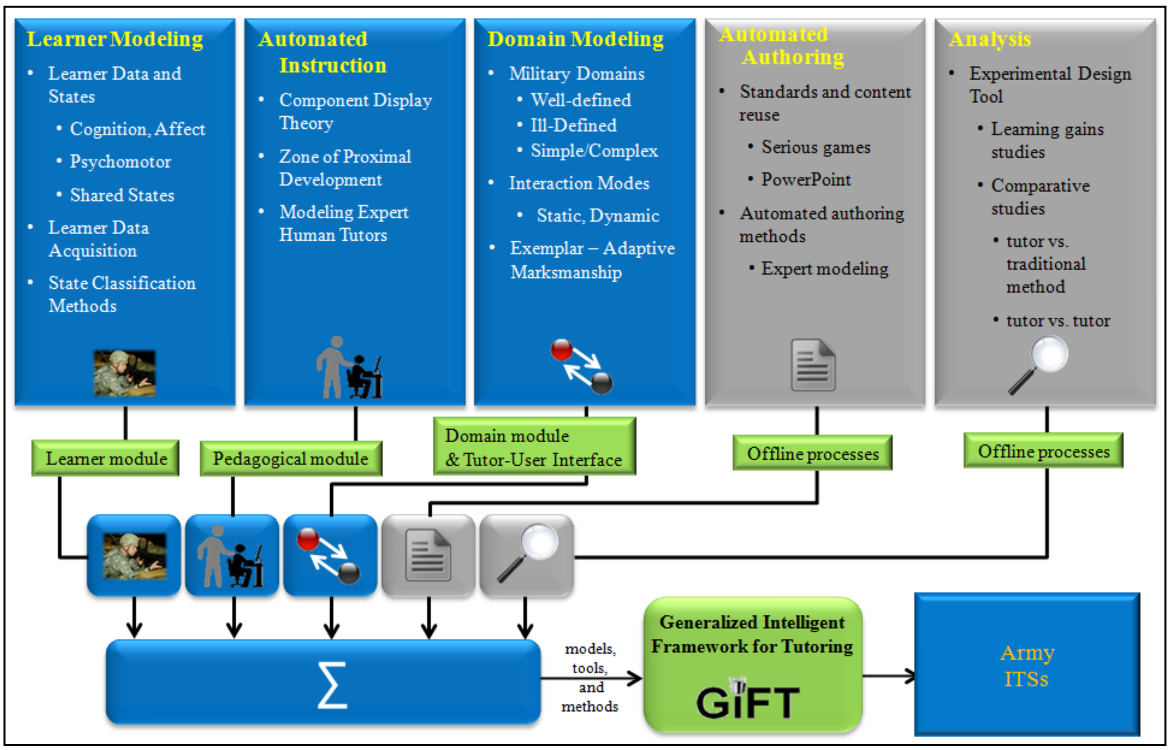

Figure 3. Adaptive tutoring research vectors.

4.1 Learner Modeling

Learner modeling may be categorized into two processes: *learner data acquisition* and *learner state classification*. The key research challenges in learner modeling are related to understanding and modeling these processes. Learner models are generally composed of learner *data*, *traits*, *and states*. Learner data generally comes from three sources: sensors, historical databases, or learner input. Learner data can vary from facts and demographics (e.g., birth dates) to raw physiological data to survey data. Traits (e.g., learning style) are defined as *habitual* patterns of behavior, thought, and emotion (Kassin, 2003). Learner states are generally derived from learner data and traits; are more transient than traits; and include the following categories (Sottilare et al., 2013):

Potential State—Also known as competence or expected success, potential is a long-term measure, which is derived from the learner's previous successful experiences, training, and education in fields related to the current training task. Success is commonly testable and measures the learner's knowledge and skill acquisition and retention.

Performance State—Contrasted with potential state or expected success, performance state measures actual learner progress toward goals. Performance is derived from learner behaviors including responses to tests/quizzes, decisions, and actions measured by speed and accuracy against potential, goals and standards to determine whether the learner is above, at, or below expectations for a given lesson, task, or concept.

Cognitive State—A measure of learner thinking capacity, problem-solving capability, and focus, the determination of cognitive states uses learner behaviors to indicate increases in complex and abstract mental capabilities (Anderson and Krathwohl, 2001). Of significance in cognitive learning are attention, engagement, and working memory. A revision of Bloom's taxonomy (Anderson and Krathwohl, 2001) tracks a series of behaviors from low-cognitive state to high as follows: remembering, understanding, applying, analyzing, evaluation, and creating.

Affective State—A measure of feeling with varying duration and relationship to identifiable sources (Gebhard, 2005), affective states include personality (long duration, multiple sources), mood (moderate duration, vague sources), and emotions (short duration, specific sources). Learner behaviors indicate affective growth and the manner in which the learner handles emotions during learning experiences and in particular when presented with significant challenges. Reported feelings, values, appreciation, enthusiasms, motivations, and attitudes indicate affective states including from low to high: receiving, responding, valuing, organizing, and characterizing (Krathwohl et al., 1964).

Motivational State—Broken out separately due to its importance in expert tutoring models (e.g., INSPIRE [Lepper et al., 1997]), motivation is influenced by goals, preferences, and interests.

Psychomotor State—Associated with physical tasks (e.g., marksmanship), which 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: perception–the ability to use sensory cues to guide motor activity; set or readiness to act; response–early stages of learning a complex skill through imitation and trial and error; mechanism–habitual learned responses; complex overt response–skillful performance of complex movements; adaptation–well-developed skills that are modified to support special requirements; and origination–the development of new movement patterns to fit unique situations.

Since Soldiers often operate in small units, it is a goal to provide an intelligent capability to support automated guided learning for teams. As part of this goal, we are researching and identifying team models including: team competency, performance, cognition, affect, trust, communication, cultural, and psychomotor state models. Other variables of interest for adaptive tutoring for teams are *context* and *culture*.

Context may be defined as "situational characteristics or events that influence the occurrence and meaning of behavior, as well as the manner and degree to which various factors impact team outcomes." Context variables include (but are not limited to) distribution, virtuality, organizational policies or procedures that impact team functioning, environmental hazards. Context is considered as an influencing condition of teamwork. This means that it is a factor that shapes the manner or degree to which teams engage in teamwork. Context is specifically important because certain situational characteristics (e.g., virtuality or distribution) have the ability to impact team outcomes or could even serve to make communication easier or more difficult.

Culture may be defined as "assumptions about humans' relationships with each other and their environment that are shared among an identifiable group of people (e.g., team, organization, nation) and manifest in individuals' values, beliefs, norms for social behavior, and artifacts." Culture is considered as an influencing condition of teamwork. Culture (either at organizational or individual levels) has the ability to shape the way that individuals view themselves in relation to the team. This, in turn, can be directly related to other important variables such as conflict, communication, or performance.

Research objectives for learner modeling include:

- expanding learner modeling beyond traditional performance modeling to include learner states previously noted in order to support truly tailored tutoring experiences;
- minimizing the number, type, and obtrusiveness of physiological and behavioral sensors required to acquire learner data in support of learner state classification;
- discovery and innovation of machine learning techniques to accurately classify learner states;
- discovery and innovation of machine learning techniques to accurately classify small team states.

4.2 Automated Instruction

The goal of automating instruction is to provide a computer-based tutor that is sufficiently adaptive to tailor training for each individual Soldier. As part of our research to realize the goal of fully automated instruction in a variety of training domains, it is useful to: examine the behaviors of successful human tutors; understand the process of instruction; and explore methods to manage instruction with the goal of keeping the learner engaged.

In examining models of expert human tutors, several themes have been identified for effective tutoring:

- demonstrate *credible knowledge* of the domain under training (e.g., tactical combat casualty care);
- read cues from the learner and adapt instruction in *real time* to meet their changing needs;
- encourage *question asking;*
- provide *indirect feedback;*
- *assess learning* often.

A review of the literature identified a set of promising models and best practices to be examined and validated through the adaptive tutoring research program. The list of models and best practices found in the following are illustrative and not exhaustive:

- *Models of expert human tutors*: INSPIRE model (Lepper et al., 1997).
- *Best tutoring practices* and facts about human tutoring (Person and Graesser, 2003).
- *Learner question asking* behaviors and the importance of questioning (Dillon, 1988).
- Relationship between *deep reasoning questions* and exam scores (Graesser and Person, 1994).
- *Politeness strategies* of tutors (Person et al., 1995).

Automated instruction can be classified into two categories of strategies: *macro-adaptive* and *micro-adaptive*. Macro-adaptive instructional strategies are informed by the learner’s traits (values, preferences, interests, and goals) and the learner’s potential state. Macro-adaptive strategies are generally implemented prior to the tutoring session to initialize the scenario. Macro-adaptive strategies influence the selection of tutoring scenarios based on their level of complexity relative to the learner’s potential. For example, a macro-adaptive strategy for a learner with low prior knowledge might be to limit the learner’s control of navigation in the learning environment. Macro-adaptive strategies do not rely on instructional context (e.g., current performance) and are domain-independent.

Micro-adaptive instructional strategies are a real-time adaptation of the initial or planned scenario and are informed by a more comprehensive model of learner states and traits. In particular, the learner's performance state is critical in selecting micro-adaptive strategies. For example, a micro-adaptive strategy during tutoring might be to assess the level of performance and provide additional navigational control as the learner demonstrates higher levels of performance. Micro-adaptive strategies are also domain-independent. This is important since pedagogical engines using domain-independent strategies may be reused across multiple training domains/tasks.

- *Error Sensitive Feedback*—an intervention triggered when the learner commits errors that are either individually or cumulatively significantly divergent from the ideal as defined in the expert model of the ITS.
- *Mastery Learning*—a strategy where the ITS ensures the learner masters (can recall and apply) prerequisite lessons or concepts before allowing the learner to move on to the next lesson/concept.
- *Adaptive Spacing and Repetition*—a strategy where the learner more easily recalls knowledge items/objects when the knowledge is exposed to the learner repeatedly over a long-time span rather than repeatedly studied during a short span of time (Dempster, 1988).
- *Metacognitive Prompting*—a strategy where the ITS encourages the learner to self-reflect and evaluate, self-explain, and self-correct rather than provide the answer directly.
- *Fading Worked Examples*—"a step-by-step demonstration of how to perform a task or how to solve a problem." (Clark et al., 2006, p. 190) from which parts have been deliberately removed or faded (Atkinson et al., 2003).

Research objectives for automated instruction are anticipated to result in:

- The creation of models of situated pedagogy to examine optimal challenge and support levels for individual learners.
- The creation of constraint-based, intelligent pedagogical agents to select appropriate domain independent strategies, select optimal tactics (actions) based on strategy selected and situational context, and then present the tactic (take action) to offer feedback, provide direction, or change the training environment.

4.3 Domain Modeling

In order to enable the capabilities of adaptive tutors to support the broad range of tasks that require training across the U.S. Army, research is needed to expand the underlying capabilities of ITS to represent tasks of varying *dynamics, definition, and complexity* as noted in figure 4. This variability in adaptive tutoring domains will allow for greater opportunities for Soldiers to *train as they fight*.

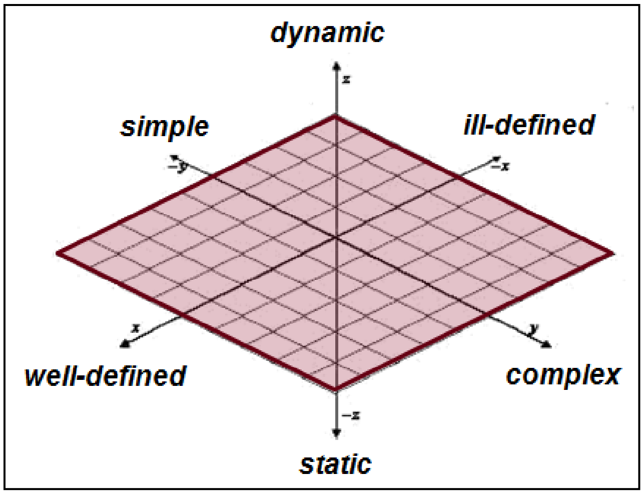

Figure 4. Domain dimensions.

Variable task dynamics refers to the physical interaction of the learner during the tutoring 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 one 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.

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.

4.4 Automated Authoring

For the purposes of this report, authoring is the creation or integration of ITSs and ITS components. The goal of automated authoring is to reduce the time and skill required to generate fully adaptive tutoring systems. Authoring tools and standards are two means to meet this goal. Authoring tools may be used to automatically produce ITSs or ITS components. Authoring tools may also support integration of existing training/tutoring environments (e.g., serious games and training simulators) to promote reuse and eliminate the need to produce the domain element of a tutoring system. Authoring tools may be used to automatically generate models (e.g., expert models) mined from existing data repositories (e.g., Carnegie Mellon's DataShop), the internet, or even field manuals. Finally, standards promoting the modularity and interoperability of ITSs, their components, tools, databases, and interfaces will go a long way toward reducing the need to author.

As part of this research, the author wants to reduce the need for authoring, and create tools and methods to make authoring easier and faster. An enhanced set of authoring goals for adaptive tutoring systems was derived from goals previously established by Murray (1999, 2003) and Sottilare and Gilbert (2011) and is presented here:

- decrease the effort (time, cost, and/or other resources) for authoring and assessing adaptive tutoring systems by establishing processes, tools, and standards for reuse;
- decrease the skill threshold required to author ITSs by tailoring tools for specific disciplines to author, assess, and employ adaptive tutoring systems;
- provide tools to aid the designer/author/trainer /researcher in organizing their knowledge;
- support (i.e., structure, recommend, or enforce) good design principles (in pedagogy and user interaction);
- enable rapid prototyping of adaptive tutoring systems to allow for rapid design/evaluation cycles of prototype capabilities;
- employ standards to support rapid integration of external training/tutoring environments (e.g., serious games) to promote learner engagement and reuse of content across learning domains (e.g., cognitive, affective, psychomotor, and social).

4.5 Analysis

An essential element of research that involves the development of models is the validation of those models to empirically establish their influence on outcomes variables (e.g., learning) and their potential for generalization across domains. To this end, a testbed to support a structured evaluation and comparison of ITS tools and methods is essential. The adaptive tutoring testbed, shown in figure 5, was adapted from the Hanks, et al. (1993) testbed and experimentation methodology.

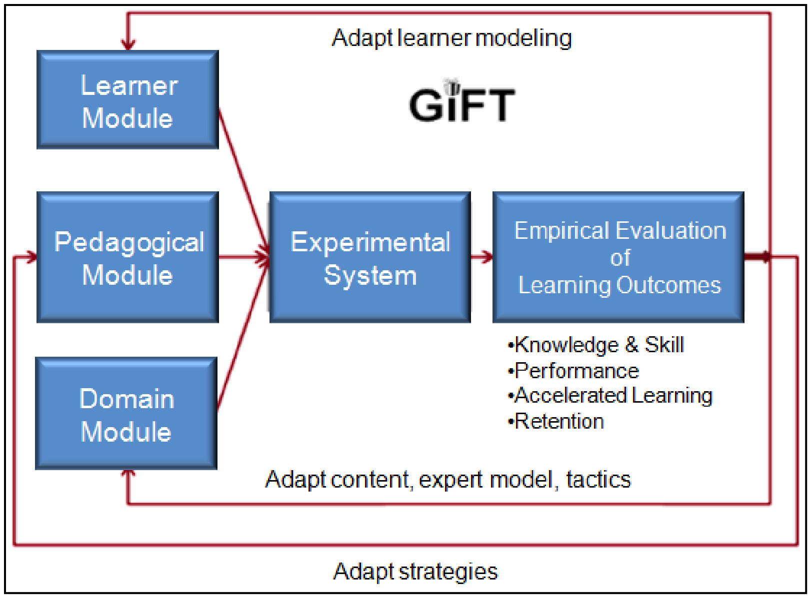

Figure 5. GIFT adaptive tutoring testbed.

The adaptive tutoring testbed will be used to assess effect size through: comparative studies, ablative studies, formative analyses, and summative analyses. Comparative studies use effect size (specifically absolute effect size) to differentiate the relative strength of methods in influencing outcomes (e.g., learning) as compared to a base case. In the case of adaptive tutoring, the traditional base case is one-to-many classroom instruction. The effectiveness of various tutoring methods in well-defined, static domains is illustrated in figure 1. The expansion of tutoring domains to align with training tasks for military operations (discussed in section 4.3 of this report) necessitates additional effectiveness evaluations to support design decisions and best practices for military tutoring systems.

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List of Symbols, Abbreviations, and Acronyms

AAR	after-action review
ALM	Army Learning Model
ARL	U.S. Army Research Laboratory
GIFT	Generalized Intelligent Framework for Tutoring
ITE	integrated training environment
ITS	Intelligent Tutoring System
S&T	Science and Technology
T&E	training and education
WFO	Warfighter Outcome

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