Use of Evidence-based Strategies to Enhance the Extensibility of Adaptive Tutoring Technologies

Benjamin Goldberg, Keith Brawner, & Robert Sottilare
Army Research Laboratory
Orlando, FL
{benjamin.s.goldberg, keith.w.brawner, robert.sottilare}@us.army.mil

Ron Tarr, Deborah R. Billings, & Naomi Malone
Institute for Simulation & Training, UCF
Orlando, FL
{rtarr, dbillings, nmalone}@ist.ucf.edu

ABSTRACT

Evolving technology continues to support increasingly advanced training systems that allow customization and personalization of content to provide instruction tailored for individual learner needs. This paper will address the identification of macro-adaptive instructional strategies for informing a generalized model of pedagogy to be implemented in a domain-agnostic Computer-Based Tutoring System (CBTS) framework. Research indicates that higher-order thinking skills are not acquired through didactic approaches but rather learner interaction with the subject matter (Shute & Psotka, 1996). Consequently, it becomes necessary to research strategies that enhance trainees' learning within computer-based platforms that allow such interaction to occur. This requires prescriptive pedagogy that tailors interaction and feedback based on trainee traits. Intelligent Tutoring Systems (ITSs) are one such application that monitors user interactions and uses Artificial Intelligence tools and methods to assess trainee performance and apply pedagogical interventions to support learning. Here, pedagogical models are responsible for informing adaptation in response to the knowledge state of users by implementing strategies intended to aid in knowledge/skill acquisition. ITSs continue to be effective instructional tools across multiple domains, yet their wide use is limited by associated development costs and lack of extensibility beyond specifically designed applications. To address these constraints, a framework is under development to provide standardized processes for authoring and applying ITS functionality across multiple training platforms and domains. Macro-adaption focuses on using learner aptitude and trait variables, measured prior to training, to inform the system regarding appropriate instructional strategies for achieving maximal learning outcomes. The intent is to utilize research-supported strategies prescribed for specific learner, knowledge, and domain conditions. These parameters will be used to construct a domain-independent pedagogical model for authoring and implementing macro-adaptive functions based on the learner's historical characteristics. The result will be a self-executing decision tree used to inform and adapt instructional strategies based on known information about the learner.

ABOUT THE AUTHORS

Benjamin Goldberg is a member of the Learning in Intelligent Tutoring Environments (LITE) Lab at the U.S. Army Research Laboratory's (ARL) Simulation and Training Technology Center (STTC) in Orlando, FL. He has been conducting research in the Modeling and Simulation community for the past four years with a focus on adaptive learning and how to leverage Artificial Intelligence tools and methods for adaptive computer-based instruction. Currently, he is the LITE Lab's lead scientist on instructional strategy research within adaptive training environments. Mr. Goldberg is a Ph.D. student at the University of Central Florida and holds an M.S. in Modeling & Simulation. Prior to employment with ARL, he held a Graduate Research Assistant position for two years in the Applied Cognition and Training in Immersive Virtual Environments (ACTIVE) Lab at the Institute for Simulation and Training.

Ron Tarr, Ph.D. is a retired Army officer and Senior Research faculty member at University of Central Florida and has an M.S. degree in Instructional Design from Florida State University. He is Program Director of the RAPTER Lab at UCF's Institute for Simulation and Training and leads a team of inter-disciplinary researchers who function as analysts, planners, integrators and designers of the advanced applications of Simulation & Learning Technologies for the purpose of enhancing human performance.

Deborah R. Billings, Ph.D. obtained an M.S. degree in Modeling and Simulation, Human Systems (2008), and a Ph.D. in Applied Experimental and Human Factors Psychology (2010) from the University of Central Florida. Dr. Billings received the 2011 Briggs Dissertation Award, presented by Division 21 of the American Psychological Association. She is currently a Post-Doctoral Researcher with the Institute for Simulation & Training.

Naomi Malone is a doctoral student at the University of Central Florida in the College of Education's Department of Educational and Human Science. She currently works as Research Assistant at UCF's Institute for Simulation & Training to identify strategies that can more efficiently train military personnel.

Keith Brawner is a researcher for the Learning in Intelligent Tutoring Environments (LITE) Lab within the U. S. Army Research Laboratory's Human Research & Engineering Directorate (ARL-HRED). He has 6 years of experience within U.S. Army and Navy acquisition, development, and research agencies. He holds an M.S.in Computer Engineering with a focus on Intelligent Systems and Machine Learning from the University of Central Florida, and is currently a Ph.D. candidate for doctoral degree in the same field. The focus of his current research is in machine learning, adaptive training, affective computing, datastream mining, and semi/fully automated user tools for adaptive training content.

Robert A. Sottilare, Ph.D. is the Associate Director for Science & Technology within the U.S. Army Research Laboratory - Human Research and Engineering Directorate (ARL-HRED) and directs research within the Learning in Intelligent Tutoring Environments (LITE) Laboratory at ARL's SFC Paul Ray Smith Simulation & Training Technology Center (STTC). He has 28 years of experience as both a U.S. Army and Navy training and simulation researcher, engineer and program manager. He leads the international program at STTC and chairs training technology panels within The Technical Cooperation Program (TTCP) and NATO. Dr. Sottilare holds a patent for a high-resolution, head-mounted projection display and his recent publications have appeared in the Educational Technology Journal, the Journal for Defense Modeling and Simulation and the proceedings of the Intelligent Tutoring Systems Conference 2010. He is a graduate of the Advanced Program Managers Course at the Defense Systems Management College, and his doctorate in modeling & simulation with a focus in intelligent systems is from the University of Central Florida. In January 2012, Dr. Sottilare was honored as the inaugural recipient of the U.S. Army Research Development & Engineering Command's (RDECOM's) Modeling & Simulation Lifetime Achievement Award. The focus of his current research is on the application of artificial intelligence tools and methods to adaptive training environments.

Use of Evidence-based Strategies to Enhance the Extensibility of Adaptive Tutoring Technologies

Benjamin Goldberg, Keith Brawner, & Robert Sottilare
Army Research Laboratory
Orlando, FL
{benjamin.s.goldberg, keith.w.brawner, robert.sottilare}@us.army.mil

Ron Tarr, Deborah R. Billings, & Naomi Malone
Institute for Simulation & Training, UCF
Orlando, FL
{rtarr, dbillings, nmalone}@ist.ucf.edu

INTRODUCTION

Adaptive training has the potential to significantly improve the effectiveness of learning interventions by accommodating individual differences and creating customized learning experiences for each individual student (Landsberg et al., 2010). Training and instructional components can be adapted based on the real-time performance of a student, but they can also be adapted based on specific learner characteristics such as aptitudes, learning preferences, and prior experiences. This further enhances adaptive mechanisms to incorporate attributes and characteristics unique to the learner. The importance of research efforts in this area is evident, especially in military contexts. Recognizing the wide variety of learner characteristics, the 2015 Army Learning Model envisions training that can be tailored to differences)such as prior performance and knowledge) to present Soldiers with individualized training at any time and in any location (TRADOC, 2011). In this paper, the authors present work for the design and development of a domain-independent pedagogical model to be applied within a Computer-Based Tutoring System (CBTS) framework. The model will inform tailoring and adaptation approaches on a generalized level for the authoring of personalized training experiences prior to system interaction.

Computer-Based Tutoring Systems

Computer-based tutoring systems (CBTSs) are applications that apply Artificial Intelligence tools and methods to assess trainee performance and direct appropriate pedagogical interventions to support learning. CBTS designers strive to create automated computer-based tutors that are as effective at personalizing the learning experience as a human tutor (Brawner & Gonzalez, 2011). A CBTS may be a viable solution to what is called the 2-sigma problem (Bloom, 1984), where students who received one-to-one human tutoring performed two standard deviations better than students in classroom environments. Therefore, it is necessary to create CBTSs based on a sound pedagogical framework to emulate the adaptability and responsiveness of a human tutor to his/her individual student's learning needs and characteristics.

Current Research

CBTSs continue to be effective instructional tools across multiple domains, yet their wide use is limited by associated development costs and lack of extensibility beyond specifically designed applications (VanLehn, 2011). To address these constraints, a framework is under development to provide standardized processes for authoring and applying CBTS functionality across multiple training platforms and domains. Here, we focus specifically on macro-adaption, which refers to the process of using learner aptitude and trait variables measured prior to training, to inform the system regarding appropriate instructional strategies for achieving maximal learning outcomes. The intent is to utilize research-supported strategies prescribed for specific learner, knowledge, performance levels, etc. These parameters will be used to construct a domain-independent (i.e., generic) pedagogical model for authoring and implementing macro-adaptive functions based on learners' historical profiles. The result will be a self-executing decision tree used to inform and adapt instructional strategies based on known information about the trainee. Such a domain-free framework would allow training platforms to display the properties of a well-designed CBTS, ultimately becoming adaptive mechanisms that provide instruction based on common pedagogical practices. This approach would enable individualized training to be developed much more quickly and efficiently, and it would reduce costs associated with researching and validating adaptive instructional strategies and pedagogical models into every new CBTS.

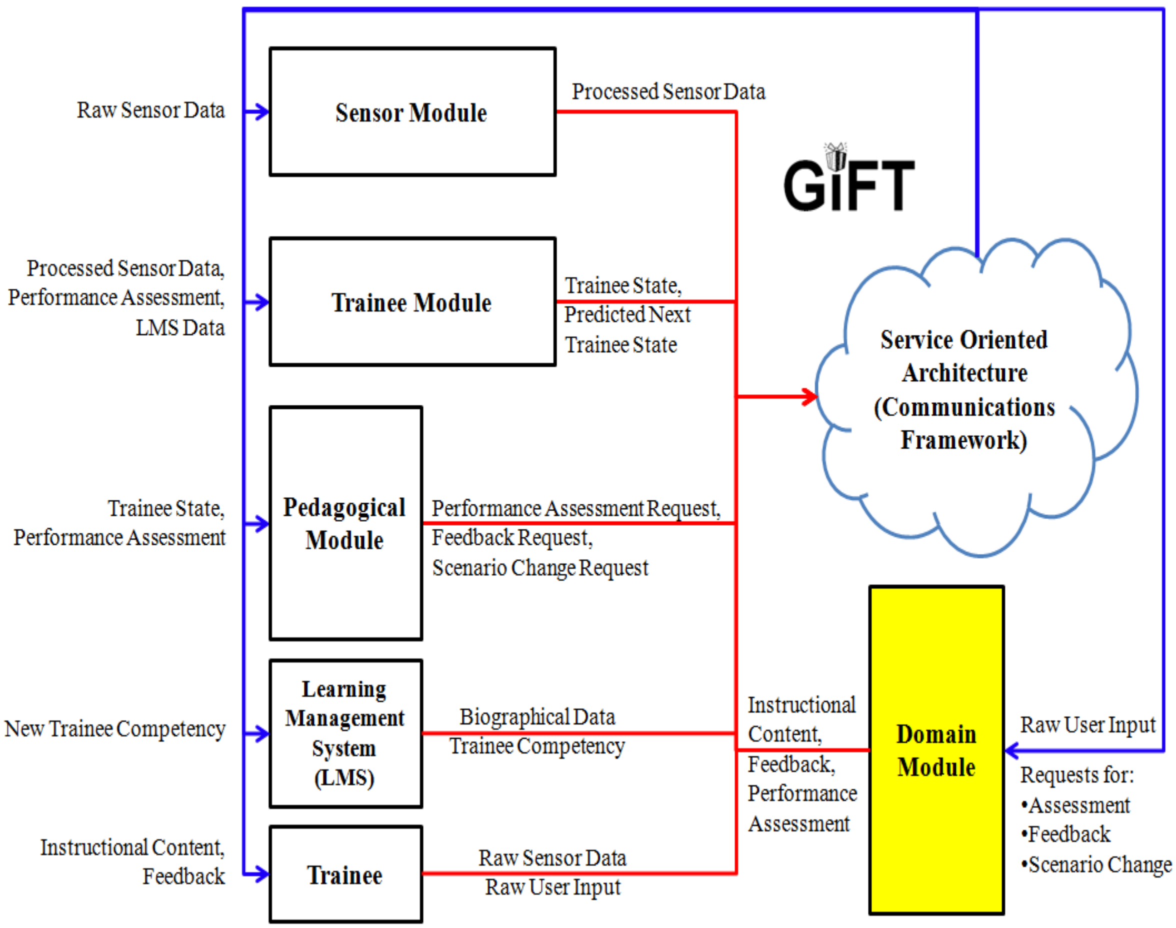

Figure 1. Generalized Intelligent Framework for Tutoring

THE GENERALIZED INTELLIGENT FRAMEWORK FOR TUTORING (GIFT)

The Generalized Intelligent Framework for Tutoring (GIFT) is the architecture under development that is driving requirements for this work (see Figure 1). It is an empirically-based, service-oriented framework designed to support the authoring and execution of pedagogical functions in a computer-based training environment. It specifically addresses the need for a reusable CBTS framework that can be extended across multiple domains and training applications, as highlighted in the Army Learning Model 2015 (TRADOC, 2011). In addition, GIFT utilizes a modular design for easy reconfiguration and serves as a test-bed to conduct impact assessments of CBTS components and methodologies. In the instructional strategy context, GIFT will serve as a test-bed for evaluating generalized models across multiple domains to assess their effectiveness and utility. The goal is for GIFT to simplify the integration of CBTS technologies in training applications both currently in use and under development through a standardized process. This enables the distribution of individualized training focused on the strengths and weaknesses associated with a given learner across multiple domains.

GIFT uses all components common to traditional CBTS implementation: (1) a learner module to track state variables specific to the learner; (2) a pedagogical module to inform instruction based on performance states communicated from the learner module; (3) a domain module that drives the training content and houses expert performance for tracing methods; (4) a sensor module for assessing state variables and a trainee's readiness to learn; and (5) a Learning Management System to store learner profiles. To maintain domain independency, all modules outside of the domain are agnostic to the knowledge and skills being trained (Goldberg, Holden, Brawner, & Sottilare, 2011). This is essential for extending the functions of GIFT into any computer-based training platform. It applies standardized messaging that links domain content to a domain-independent concept map and to a pedagogical framework that manages instruction.

GIFT provides tailoring and adaptation in two phases. First, dependent on what is being trained and who is being trained, offline processes will tailor content based on an individual's prior knowledge, attributes, and abilities prior to system interaction. Following, the system guides and adapts instruction as an individual progresses through a training session via state messages, communicated between modules in real-time. An authored system will track predetermined performance objectives key to skill development and affective/cognitive states that have been found to impact performance outcomes through behavioral and physiological sensing technologies. GIFT tracks performance to determine training concepts that need attention and affective/cognitive states deemed negative to learning (e.g., boredom, frustration, anger, disengagement, etc.). The pedagogical model will then use this information to prescribe empirically-based guidance or adaptation techniques informed from sound instructional design research. A key challenge associated with a domain-agnostic design is structuring a generalized pedagogical approach that can be applied across domains and platforms. In this function, the pedagogical module determines appropriate instructional strategy implementation based on attributes specific to both the individual and content being trained.

Pedagogical Model

Traditionally, a pedagogical model in a CBTS informs explicit execution of feedback and adaptation based on an individual's performance within a defined problem space. Theories of education provide an empirical basis for identifying variables that influence learning and a pedagogical framework describes the principles through which theory is applied (Mayes & Freitas, 2004). Specifically, a pedagogical model is designed to balance the level of guidance a student needs with the goal of maintaining engagement and motivation (Beal & Lee, 2005). This requires tailoring content to an appropriate challenge level prior to system interaction along with tracking performance in real-time to intervene when parameters exist that warrant an interruption. To this effect, a pedagogical model manages training practices by adapting content to the knowledge and abilities of a single user, and providing real-time guidance and feedback based on system interactions. There are many opinions out there on what strategies are best and when they are most appropriate; it is the pedagogical model that defines the rules and conditions they are executed under.

Pedagogical models in a CBTS are customarily informed by strategies that expert tutors and instructors can use to assist individuals in learning (Beal & Lee, 2005; Person & Graesser, 2003), and are typically developed as a one-fit solution to the system they operate within. This requires a system to be able to recognize errors in performance, determine the root cause or misconception linked to that error, and implement an instructional strategy in real-time to mitigate negative outcomes. This closed-loop process is dependent on the training application the system is acting on, and strategies authored are tied directly to the training domain. This bounds their application and extensibility to the specific domain they are modeled to train (VanLehn, 2011). Due to this constraint, CBTS developers are required to spend a large amount of time and effort to author guidance and adaptive functions for a single platform (Woolf, 2009).

In recognition of the desire to ease the process of authoring adaptive capabilities in training platforms, GIFT's pedagogical module is designed to inform tailoring and intervention approaches through empirically-based instructional strategies that are generic in nature. That is, strategies selected are focused on high-level processes that highlight their theoretical purpose and intent for application. It uses attribute data (highlighted below) associated with the user and domain to determine recommended strategies based on pedagogical theory. Instructional strategies will be identified that form the foundation of the domain-independent pedagogical model used in the GIFT framework. Ultimately, the pedagogical model will serve as an authoring tool to select generalized strategies along with guidelines that will assist a trainer in authoring the specific tactic to implement. Here, we explore a macro-adaptive approach to instructional strategies, which allows tailoring of the instruction.

Macro-adaptive Approach

Several different approaches to implementing adaptive training exist: the macro-adaptive approach, the Aptitude Treatment Interaction (ATI) approach, and the micro-adaptive approach. Macro strategies structure an organized and sequential set of tactics (to be implemented online) and address four instructional design areas: selection, sequencing, synthesizing, and summarizing (Reigeluth, 1999). This approach generally focuses on the sequencing of instruction and the degree of learner control, based on metrics collected prior to the commencement of training (Landsberg et al., 2010). Here, instructors categorize students prior to training, typically based on formal assessments of the student's instructional goals, general ability, and achievement levels (Park & Lee, 2004; Spain, Priest, & Murphy, 2012). Pre-planned adaptive interventions (i.e., what to adapt and how to adapt) are then implemented for the different groups (Spain, Priest, & Murphy, 2012). Examples of macro-adaptive instructional interventions include: breadth or depth of content, content difficulty, sequencing of content, type of media used to present content, number of practice problems, and type and specificity of feedback (Spain, Priest, & Murphy, 2012). In the macro-approach, the selected instructional tactic aligns with both the strengths and weaknesses of the groups (see Figure 2 on next page).

The ATI approach is very closely related to the macro-adaptive approach in that it focuses on adapting instructional tactics to individual learner characteristics and individual differences (e.g., intellectual ability, learning styles, and prior knowledge; Landsberg et al., 2010). In this way, the ATI approach categorizes students based on specific learner characteristics and presents the most effective instruction for that particular group. From this description, it appears there is much crossover between macro-adaptive and ATI approaches. However, macro-adaptive instruction always tailors instruction before training begins. Conversely, the ATI approach can involve tailoring instruction before training begins, and it can also be used to personalize instruction during training (Landsberg et al., 2010). These two methods are the primary focus for the initial generalized pedagogical model commented on in this paper.

Finally, instruction can be modified using a micro-adaptive approach, in which task performance and learning needs are monitored in real time. Micro-adaptation uses system performance metrics and learner state variables to assess progress, reaction to training and adapt instruction in real-time (Landsberg et al., 2010; Park & Lee, 2004). These strategies focus on guidance and feedback within a problem space and are triggered through specific actions taken in the system. Despite the adaptive functions a system can perform, understanding how people learn and how individual differences affect the way they learn is essential in authoring effective adaptive training. For this purpose tools must be in place that assist training developers in identifying and integrating sound instructional strategies into their training applications.

IDENTIFICATION OF INSTRUCTIONAL STRATEGIES

The term ‘instructional strategy’ encompasses a continuum ranging from organizers that structure instructional objectives (e.g., Bloom’s taxonomy) to simple instructional tactics (e.g., chunking or fading) that are chosen based on these objectives (Jonassen & Grabowski, 1993, Arends & Castle, 2002). Instructional strategies fall in the middle of this continuum and consist of a series of steps or events, usually supported by theory and research (Hirumi, 2010, Arends & Castle, 2002). Further, many instructional strategies can be grouped according to general approaches (e.g., learner-centered, teacher-centered, or experiential). Simulations are instructional strategies rooted in established theories and research in human learning that are generally associated with experiential approaches (Hirumi, 2010). Designing instruction is a complex endeavor involving numerous inputs and variables. Therefore, it may be a useful exercise to group and situate individual tactics within specific instructional strategies to conceptualize them as building blocks that can be constructed according to the needs of specific learning objectives, instructional strategies, and the variables associated with them.

This current effort utilizes research (for The Office of Naval Research and the Marine Corp) that investigated instructional strategies to enhance training. That study organized instructional strategies and tactics taken from research literature into a web/search application built to assist training developers and instructors with multimedia and simulation-based training. Using that work as a baseline, the research team is investigating empirically-examined instructional strategies and tactics relevant to macro-adaptation and intelligent tutoring for the GIFT program.

Macro-Adaptive Instructional Strategies

Macro-adaptive, as well as some ATI instructional tactics comprise the focus of the current research effort. Instructional tactics that can be adapted based on metrics collected prior to training (i.e., metrics that place students into different groups, depending on certain characteristics) are currently being investigated. In particular, the current research effort is most interested in research supporting macro-adaptive instructional tactics that are applicable to computer-based training applications.

A literature review was conducted using *Google Scholar*, *PsycINFO*, *Academic Search Premier*, *Education Full Text (H. W. Wilson)*, *Education Index Retrospective: 1929-1983 (H. W. Wilson)*, and *ERIC* databases. Additionally, we performed searches within *ProQuest (Dissertation and Thesis Search)*. The following keywords were initially used to conduct searches: *macro-adaptive, individual differences, pedagogy, goal-orientation, self-efficacy, trait, individualized instruction, tailored instruction, personalized instruction,* and *Interactive Multimedia Instruction (IMI)*. Both empirical and theoretical papers which described instructional strategies and tactics that could be adapted to learners were collected for further review. Several sources and targets of adaptation were identified from the body of literature.

Sources of Adaptation

Sources of adaptation refer to the factors that prompt, or trigger, adaptation to occur, namely the characteristics of learners that elicit specific instructional tactics to be implemented. In other words, the sources of adaptation represent different groupings that students can be assigned to prior to training. To date, in our review of the literature, we have identified several different categories for sources of adaptation at the macro-level (see Figure 2). Targets of adaptation refer to "what" instructional components are adapted, based on the sources of adaptation. We have also identified several different categories of these targets for inclusion in our research.

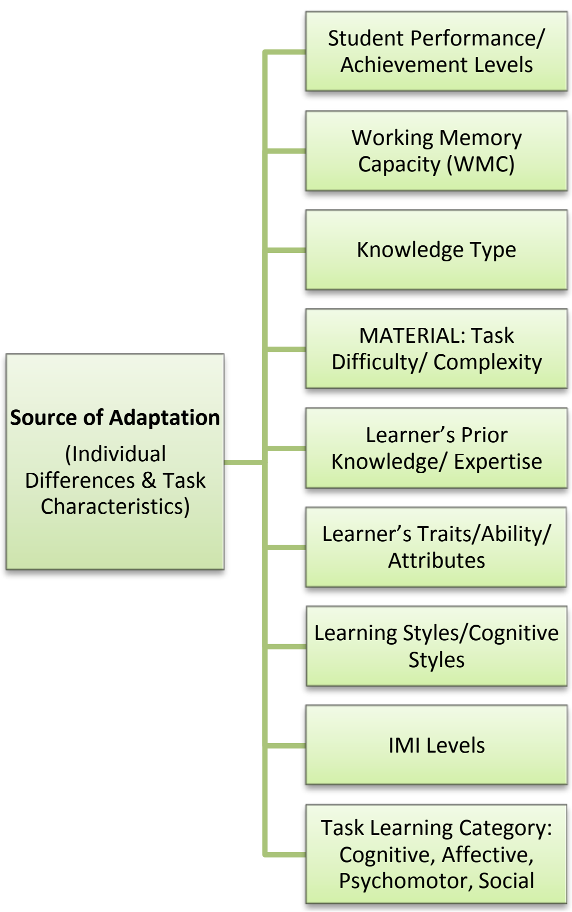

Figure 2. Identified sources of adaptation in the literature to date

Targets of Adaptation

Different sources of adaptation appear to be linked with different targets of adaptation (see Figure 3) in the literature. For instance, depending on the level of student performance and achievement, different types of feedback may be more effective than others (Shute, 2008). Working memory capacity has also been cited as integral to adapting instruction, and in particular can be used as a guideline for sequencing and segmenting instruction based on the capacity of each individual student (Lusk et al., 2008). Another source of adaptation is knowledge type (e.g., procedural or theoretical), which can impact the success of different methods of sequencing instructional components (Van Patten, Chao, & Reigeluth, 1986). Task difficulty and complexity have also been identified as sources of

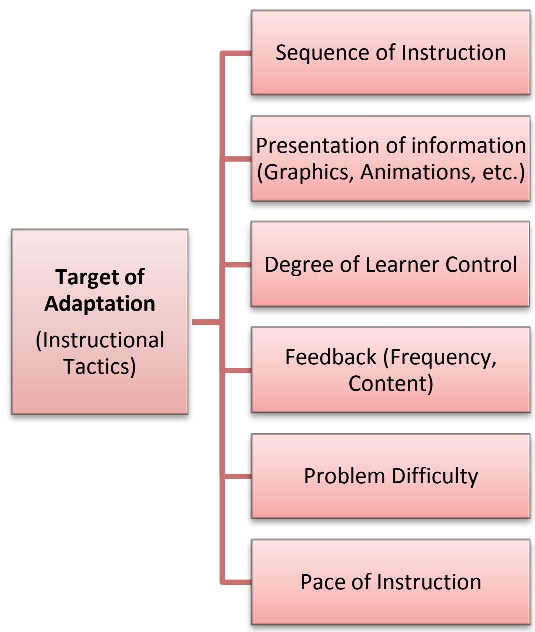

Figure 3. Identified targets of adaptation in the literature to date

adaptation. For example, the optimal level of guidance given during instruction may depend on the initial difficulty of the task or content of instruction (Van Merrienboer, Kester, & Paas, 2006). A learner's prior knowledge or expertise of the instructional content can affect the most effective methods of presenting feedback to the learner, as well as the level of guidance to give throughout training (Smits et al., 2008). Also, a learner's traits, abilities, and aptitudes can determine the most efficient level of control to give students over their own instruction (Amadieu et al., 2009). Learning and cognitive styles, although controversial constructs, may provide valuable insight into the most effective ways to adapt feedback, level of learner control, and the amount of guidance to each individual learner based on his or her cognitive style (Triantafillou et al., 2004). Finally, Interactive Multimedia Instruction (IMI) levels can impact the effectiveness of certain instructional tactics (Campbell et al., 2006; Schatz et al., 2012). IMI levels "…describe how much interactivity is possible in a piece of instructional media, such as an educational video or a training simulation" (Schatz et al., 2012, p. 191).

APPLICATION OF MACRO-ADAPTIVE STRATEGIES

Specific instructional tactics and "best practices" found in the literature will be translated into recommendations for the generic framework for intelligent tutoring system design. Design guidelines will incorporate information relating to "how" to adapt instruction to effectively tailor it to individual students. These will then be incorporated in the GIFT framework and subjected to empirical testing to determine the efficacy of using recommended macro-adaptive instructional tactics across multiple learning domains.

Development of Decision Tree

The concept of a decision tree was originally developed for the purpose of decision support. The idea behind it is that a series of branching pathways built from initial variable input are able to produce the ideal behavior of a network. This is then built from a series of thresholds or tests. An example of this can be found in animal classification tests, where descriptive inputs such as fur, egg-laying, scales, and feathers can place animals in categories of mammalian, reptilian and avian.

A decision tree is usually built alongside a model of probability or entropy. The early nodes of the tree should be the most descriptive of the data. This field intersects with the field of AI in the arena of optimal decision tree construction. In many aspects of artificial intelligence the aim is to optimize the decision process to be efficient, and decision tree construction is not significantly different. With AI, a decision tree is typically optimized towards one of two goals: the minimization of entropy, or the maximization of the likelihood. Decision trees created relating to instructional design have two potential chokepoints. The first point of contention is the ability to garner learner data. For example, basing a decision on a learner's Intelligence Quotient (IQ) takes 15 minutes to assess. This may not be practical when assessing a classroom of 40 students, which could take a combined 10 hours. Instructional strategy recommendation decision trees should optimize towards decision points which are easily collected.

The other, more significant, bottleneck of decision tree creation is the generation of types of feedback. Eventually, the final part of the process of student trait and task type evaluations is a decision. This decision, as shown in Figure 4 may be to change difficulty, pace, sequence, or presentation of instruction. Conceivably, each of these decisions could be broken down into three or more different levels (e.g., easy/medium/hard problems; slow/medium/fast instructions). However, at some level, a content author is required to create this level of feedback in order to respond to the instructional strategy request. Optimization towards the minimum set of intervention types is desirable in order to reduce the load on content creators. To this effect, attributes associated with the training content (knowledge type, difficulty/ complexity, etc.) will be used to organize a bank of strategies associated with these characteristics. This will slice the identified strategies into a manageable list to be used by authors and system developers. In turn, characteristics and attributes associated with the user will be used to select an optimal strategy out of the associated bank.

Illustrative Example of GIFT

Here, we illustrate how the generic framework will be applied to a CBTS and outline a use case process that will ultimately generate the most appropriate instructional tactics. Figure 4 depicts this process graphically, from inputs needed prior to training to the implementation of the appropriate instructional strategies. It also shows an overview of how the human instructor will interact with the system.

Prior to training, there are several different types of information that need to be entered into the framework (i.e., input by the instructor or course developer):

1. The instructor enters training content into GIFT and develops suitable learning objectives for the task training.
2. The instructor designates each learning objective as a specific knowledge type (e.g., declarative, integrative, conceptual, procedural).
3. The learner is assessed according to several pre-determined characteristics (e.g., knowledge level, prior experience on this particular training task, motivation, goal orientation, etc.).

The GIFT system takes these inputs made prior to training and generates a collection of instructional

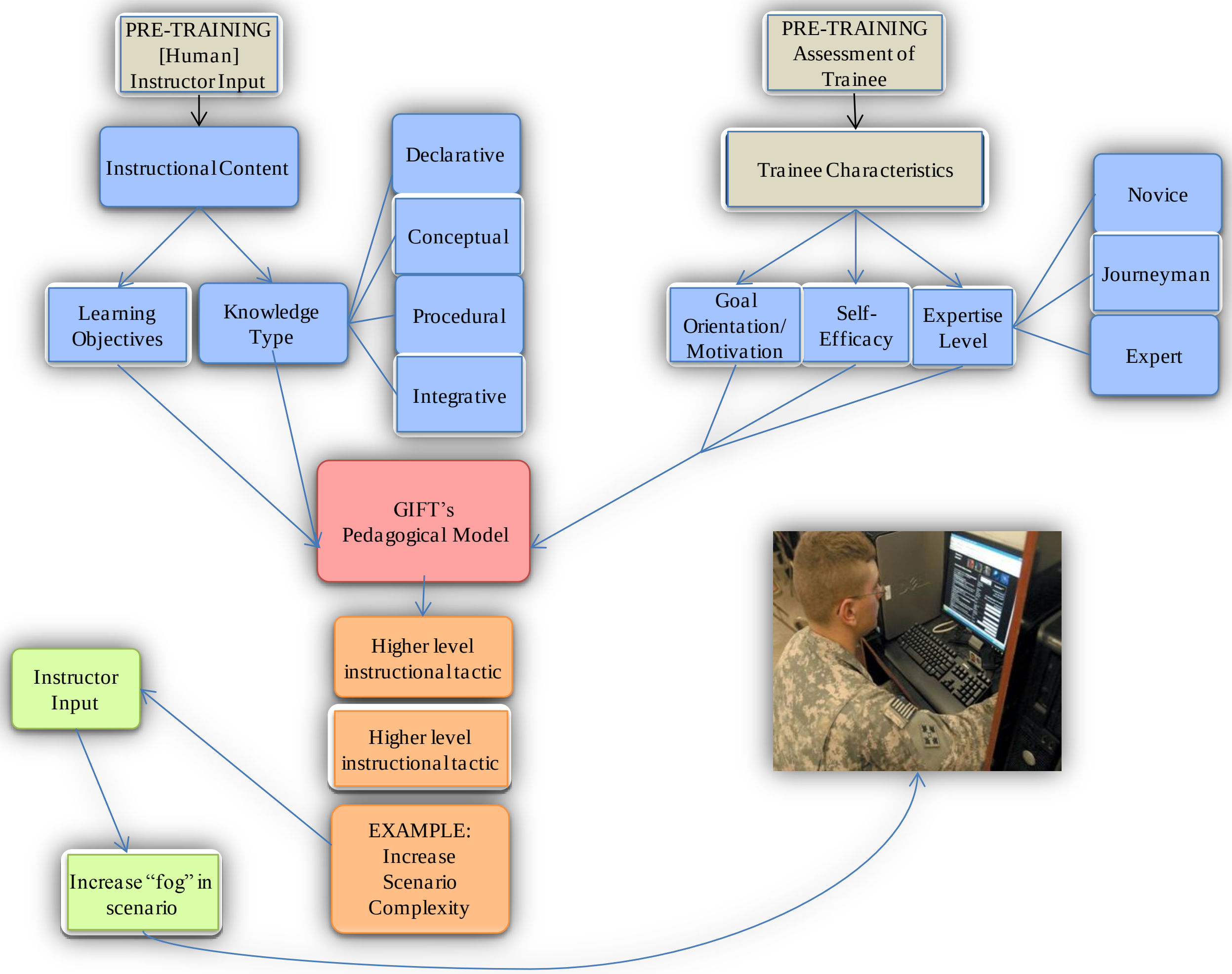

Figure 4. Process used to generate appropriate macro-instructional tactics in GIFT

tactics for the CBTS to incorporate. Essentially GIFT acts as an instructional designer or authoring tool so that the human instructor does not need to possess this knowledge in order to administer effective training. GIFT generates, for each specific learner, a complete instructional strategy/program/plan to follow, based on the recommendations programmed into the pedagogical model. The pedagogical model contains recommended and empirically supported instructional tactics that facilitate effective learning. Particular tactics from this model are chosen, depending on the individual learner needs and characteristics; therefore, each instructional strategy may be slightly different. The instructional tactics from GIFT's pedagogical model then guide the CBTS in how it presents and administers training. The human instructor is responsible for adding content to these instructional tactics.

To illustrate the operability of the framework and the CBTS, consider the following simple scenario. Imagine that we want to train a novice to perform a certain task. We then input the information about the expertise level into the GIFT framework, which then communicates with the pedagogical model. A novice learner benefits from detailed feedback on the learning objective. This instructional tactic is drawn directly from the pedagogical model and applied to the training. The instructor would then receive a prompt asking him/her to input detailed feedback for this particular task. After inputting the necessary prompts, the CBTS would begin training. The GIFT framework would not only be adapting training to inputs made prior to training (macro-approaches), but it would also be continuously assessing learner performance, mood, etc., and would adapt to ongoing changes in learner characteristics (micro-adaptive approaches). For more experienced learners, an appropriate strategy may be to increase the complexity of the problem or scenario (see Figure 4). Here, GIFT would prompt the instructor to increase the complexity, but the instructor would ultimately decide how this would be implemented in the system (e.g., to increase the fog in the virtual environment of a reconnaissance training mission). While to date, we have only explored macro-adaptive strategies, the micro-adaptive strategies will be explored in future research efforts.

Extensibility of GIFT

One of the significant research questions that GIFT seeks to answer via experimentation is the viability of various types of instructional strategy decisions for an individual. Presumably, the correct decision is the one which consistently increases learning on the topic, while keeping the trainee interested in this learning. Research suggesting that there is little evidence for adapting instruction based on learning styles (Pashler, McDaniel, Rohrer, & Bjork, 2008) can easily be empirically evaluated in this type of framework. As an example, an experimenter could create two instructional engines which consistently tailor content in accordance with learning style theory and practice..

Furthering this type of research is the idea that experimental control can be maintained. Each module may be seamlessly interchanged as part of the experimental design, while keeping the training content, interactions, student models, and sensors static. This provides a valuable experimental framework for drawing novel conclusions.

Additionally, a system such as GIFT is extensible to multiple domains through the engineering trade-off of requesting non-domain-specific instructional interventions. This allows for the creation of one instructional strategy engine which is able to inform multiple simulators, games for training, or other types of instructional content presentation systems. One instructional designer is able to create a system which is able to be experimentally validated against others, and able to train multiple tasks across vastly diverse populations of interest.

Additional research is needed to develop best practices and select "best in class" models and functions for incorporation in GIFT. There continues to be much debate about the influence of individual differences (e.g., learning styles, personality) on informing tailored instructional strategy decisions and thereby learning outcomes. Future CBTS research should address the impacts of individual differences on accelerated learning and retention (Sottilare and Goldberg, 2012), small unit tutoring (Sottilare, Holden, Brawner and Goldberg, 2011), mobile learning, and other self-regulated learning outcomes and modalities. Retention raises the bar for CBTS expectations in that future tutoring systems will also require a long-term model of the learners to understand their capacity to retain information and recommend spacing and frequency of tutoring for specific domains.

CONCLUSION

Many of the best CBTSs provide a 1-sigma learning gain, have limited perception and "understanding" of the learner's states and traits, and/or have limited capacity to use learner data to drive pedagogical decisions. This paper addressed macro-adaptive instructional strategies to inform a generalized model of pedagogy for a domain-agnostic CBTS framework. Informing micro-adaptive (in-situ) strategies is still more challenging. In order to provide timely and relevant feedback, real-time or near real-time assessments of the learner's cognitive and affective states may be needed to support micro-adaptive strategy decisions. The accuracy of these state assessments will be critical in providing optimal feedback to enhance learning. The CBTS will also be required to assess and interpret multi-sensor data inputs, and track learner performance against expectations (e.g., standards) to adapt the tutoring session and optimize learning.

To move toward and beyond Bloom's 2-sigma learning gain, CBTS will require an assessment framework to empirically evaluate the effect of CBTS structure and function. Learner models, task analysis, and pedagogical strategies and tactics are among the CBTS structures and functions to be evaluated andvalidated. To this end, GIFT has been developed as a service-oriented architecture to support comparative evaluations of CBTS structure, tools and methods including the effect of macro-adaptive strategies and tactics on learning gain. GIFT 1.0 was released in May 2012 to the Department of Defense (DoD) and DoD contractors and may be requested via GIFTtutoring.org. It is envisioned that future versions of GIFT will evolve based on the contributions of the GIFT user community.

REFERENCES

Amadieu, F., Van Gog, T., Paas, F., Tricot, A., & Marine, C. (2009). Effects of prior knowledge and concept-map structure on disorientation, cognitive load, and learning. *Learning and Instruction, 19*, 376-386.

Arends, R.I., & Castle, S. (2002). Instructional strategies. *Encyclopedia of Education*. Retrieved from http://www.encyclopedia.com/doc/1G2-3403200320.html.

Beal, C., & Lee, H. (2005). *Creating a pedagogical model that uses student self reports of motivation and mood to adapt ITS instruction*. Retrieved from http://w3.sista.arizona.edu/~beal/publications/files/Beal&LeeCRC.pdf.

Bloom, B. (1984). The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring, *Educational Researcher*, *13*(6), 4–16.

Brawner, K.W., & Gonzalez, A. (2011, September) *Realtime clustering of unlabeled sensory data for trainee state assessment.* Paper presented at the International Defense and Homeland Security Simulation Workshop, September 2011, Rome, Italy.

Campbell, C., Cantrell, G., Generalao, T., Sawyer, A., & Takitch, J. (2006). Interactive multimedia instruction for US Army training. In T. Reeves & S. Yamashita (Eds.), *Proceedings of World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education 2006* (pp. 1105–1110). Chesapeake, VA: AACE.

Goldberg, B. S., Holden, H. K., Brawner, K. W., & Sottilare, R. A. (2011). *Enhancing Performance through Pedagogy and Feedback: Domain Considerations for Intelligent Tutoring Systems*. Paper presented at the Interservice/Industry Training, Simulation, and Education Conference (I/ITSEC) 2011, Orlando, FL.

Hirumi, A. (2010). Grounded instructional strategies. [Course handout]. Retrieved from EME6133 Blackboard site.

Jonassen, D.H., & Grabowski, B.L. (1993). *Handbook of Individual Difference, Learning, and Instruction.* Hillsdale, NJ: Lawrence Erlbaum Associates, Publishers.

Landsberg, C. R., Van Buskirk, W. L., Astwood, R. S., Jr., Mercado, A. D., & Aakre, A. J. (2010). *Adaptive training considerations for use in simulation-based systems*. Special Report 2010-001. Office of Naval Research. Retrieved from http://www.dtic.mil/dtic/tr/fulltext/u2/a535421.pdf.

Lusk, D. L., Evans, A. D., Jeffrey, T. R., Palmer, K. R., Wikstrom, C. S., & Doolittle, P. E. (2008). Multimedia learning and individual differences: Mediating the effects of working memory capacity with segmentation. *British Journal of Educational Technology*, *40*(4), 636-651.

Mayes, T., & Freitas, S. d. (2004). Review of e-learning frameworks, models and theories. *JISC e-Learning Models Desk Study*, Available online from http://www.jisc.ac.uk/epedagogy/

Reigeluth, C.M. (1999). The elaboration theory: Guidance for scope and sequence decisions. In C.M. Reigeluth (Ed.), *Instructional-Design Theories and Models: A New Paradigm of Instructional Theory.* (Volume II). Hillsdale, NJ: Lawrence Erlbaum Assoc.

Park, O., & Lee, J. (2004). Adaptive instructional systems. In D. H. Jonassen (Ed.), *Handbook of research on educational communications and technology* (2nd ed., pp. 651–684). Mahwah, NJ: Lawrence Erlbaum Associates.

Pashler, H., McDaniel, M., Rohrer, D., & Bjork, R. (2008). Learning styles: concepts and evidence. *Psychological Science in the Public Interest*, 9(3), 105–119.

Person, N. K., & Graesser, A. C. (2003). Fourteen Facts about Human Tutoring: Food for Thought for ITS Developers. In V. Aleven, U. Hoppe, J. Kay, R. Mizoguchi, H. Pain, F. Verdejo & K. Yacef (Eds.), *Artificial Intelligence in Education 2003 Workshop Proceedings on Tutorial Dialogue Systems: With a View Toward the Classroom* (pp. 335-344). Sydney, Australia

Schatz, S., Oakes, C., Folsom-Kovarik, & Dolletski-Lazar, R. (2012). ITS + SBT: A review of operational situated tutors. *Military Psychology*, *24*(2), 166-193.

Shute, V.J. (2008). Focus on formative feedback. *Review of Educational Research*, *78*(1), 153-189.

Shute, V. J., & Psotka, J. (1996). Intelligent tutoring systems: Past, present, and future. In D. Jonassen (Ed.), *Handbook of research for educational communications and technology* (pp. 570-600). New York, NY: Macmillan.

Smits, M. H. S. B., Boon, J., Sluijsmans, D. M. A., & Van Gog, T. (2008). Content and timing of feedback in a web-based learning environment: Effects on learning as a function of prior knowledge. *Interactive Learning Environments*, *16*, 183-193.

Spain, R. D., Priest, H. A., & Murphy, J. S. (2012). Current trends in adaptive training with military applications: An introduction. *Military Psychology*, *24*(2), 87-95.

TRADOC (2011). The U.S. Army learning concept for 2015. TRADOC PAM525-8-2. Retrieved from http://www-tradoc.army.mil/tpubs/pams/tp525-8-2.pdf

Triantafillou, E., Pomportsis, A., Demetriadis, S., & Georgiadou, E. (2004). The value of adaptivity based on cognitive style: An empirical study. British *Journal of Educational Technology*, *35*(1), 95-106.

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems, *Educational Psychologist*, *46*(4), 197-221.

Van Merrienboer, J. J. G., Kester, L., & Paas, F. (2006). Teaching complex rather than simple tasks: Balancing intrinsic and germane load to enhance transfer or learning. *Applied Cognitive Psychology*, *20*, 343-352.

Van Patten, J., Chao, C.I. & Reigeluth, C.M. (1986). A review of strategies for sequencing and synthesizing instruction. *Review of Educational Research, 56*(4), 437-4.

Woolf, B. P. (2009). *Building Intelligent Interactive Tutors: Student-Centered Strategies for Revolutionizing E-Learning*. Burlington, MA: Morgan Kaufmann.