Adapting Existing Simulation Architectures to Enhance Tailored Instruction

Robert A. Sottilare, Ph.D., Ross Hoehn, Ph.D. and Alyssa Tanaka, Ph.D.
Soar Technology, Inc.
Orlando, Florida
{bob.sottilare, ross.hoehn, alyssa.tanaka}@soartech.com

ABSTRACT

This paper examines the theory, design, application and recommended standards associated with adaptive instructional systems (AISs) as drivers for tailoring military training in simulation environments. Most military simulations today are classified as minimally adaptive in that they modify content only based on learner/team performance, and generally do this in a prescriptive way. AISs are artificially-intelligent, computer-based systems that guide learning experiences by tailoring instruction and recommendations based on the goals, needs, and preferences of each individual learner or team in the context of domain learning objectives. AISs come in several forms including intelligent tutoring systems (ITSs), intelligent mentors (e.g., recommender systems), and intelligent media. The most common AIS components are domain models, learner models, instructional models and interface models. Adaptive instruction is desired as a military training tool to improve training efficiency (e.g., accelerate learning) by intelligently focusing tutoring resources where they are needed most - on gaps in learner knowledge and skill. Both US Army Synthetic Training Environment and US My Navy Learning programs have design goals to enable adaptive instruction. Adaptive instruction has been a topic of research for decades and AIS architectures such as the Generalized Intelligent Framework for Tutoring (GIFT) have been used to demonstrate the efficacy of tailoring simulation-based military training (e.g., Virtual BattleSpace – VBS) to optimize learning outcomes. However, the principles needed to automatically tailor training within existing military training systems have not been fully described nor generalized. This paper ties together instructional theory and design principles needed to seamlessly integrate AISs with military training simulations with the goal of enabling AISs to automatically tailor instruction in real-time. To realize a fully enabled AIS for military simulations, we have identified components, models, functions, gateways, and data exchange requirements to support both syntactic and semantic interoperability.

ABOUT THE AUTHORS

Dr. Robert Sottilare is the Science Director for Intelligent Training at Soar Technology, Inc. He came to SoarTech in 2018 after completing a 35-year career in federal service in both Army and Navy training science and technology organizations. At the US Army Research Laboratory, he led the adaptive training science and technology program where the focus of his research was automated authoring, instructional management, and analysis tools and methods for intelligent tutoring systems (ITSs) and standards for adaptive instructional systems. He is a co-creator of the Generalized Intelligent Framework for Tutoring (GIFT), an open source, AI-based adaptive instructional architecture. Dr. Sottilare is a recipient of the US Army Meritorious Service Award (2018; 2nd highest civilian award), the US Army Achievement Medal for Civilian Service (2008; 5th highest civilian award), and two lifetime achievement awards in Modeling & Simulation: US Army RDECOM (2012; inaugural recipient) and National Training & Simulation Association (2015). He is lifetime member of the National Defense Industry Association.

Dr. Ross D. Hoehn is a research scientist in Soar Technology's Intelligent Training division. He earned his Ph.D. in Theoretical Chemistry from Purdue University in 2014, and continued research in chemical physics, quantum information and artificial intelligence until 2018 when he joined SoarTech. His research areas include: adaptive artificial intelligence, generative AI techniques, team learning and training, pedagogy, biological-based agent simulations, swarm mechanics, quantum information science, quantum computing and quantum mechanically-driven biophysical phenomenon. He was an active researcher and manager of the NSF Center for Chemical Innovation: Quantum Information for Quantum Chemistry, a multi-million-dollar, multi-year research effort centered at Purdue University to utilize quantum computing for quantum mechanical calculations.

Dr. Alyssa Tanaka has worked with Soar Technology as a Research Scientist since April 2017. She has earned a Ph.D. and M.S. in Modeling and Simulation from the University of Central Florida, Graduate Certificates in Instructional Design and Training Simulations, and a B.S. in Psychology and Cognitive Sciences from the University of Central Florida. She also holds a diploma in robotic surgery from the Department of Surgery, University of Nancy, France. Before joining SoarTech, Dr. Tanaka led research initiatives directly related to improving the training and education of robotic surgeons through simulation as a Senior Research Scientist at Florida Hospital Nicholson Center, the premier location in the world both for training expert practitioners with the daVinci surgical robot and for advancing research in cutting-edge training to target this device. At SoarTech, she leads the initiatives aimed at leveraging AI and Intelligent Training solutions into the military medical community.

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INTRODUCTION

This paper examines the theory, design, application and recommended standards associated with developing adaptive instructional systems (AISs) as drivers to tailor military training in simulation-based environments. Most military simulations today are categorized as minimally adaptive in that they modify content based only on learner/team performance, and generally do this in a very prescriptive way. AISs are artificially-intelligent, computer-based systems that guide learning experiences by tailoring instruction and recommendations based on the goals, needs, and preferences of each individual learner or team in the context of a set of domain learning objectives (Sottilare & Brawner, 2018). AISs come in several forms including intelligent tutoring systems (ITSs), recommender systems, and intelligent media (Figure 1). ITSs are computer-based instructional tools that help learners master knowledge and skills by using intelligent algorithms to tailor training for each learner (Graesser, Hu, Nye, & Sottilare, 2016; Graesser, Hu, and Sottilare). ITSs traditionally instruct one learner at a time, but emerging capabilities are anticipated to support automated instruction for groups of collaborative learners, teams of learners, and ultimately teams of teams.

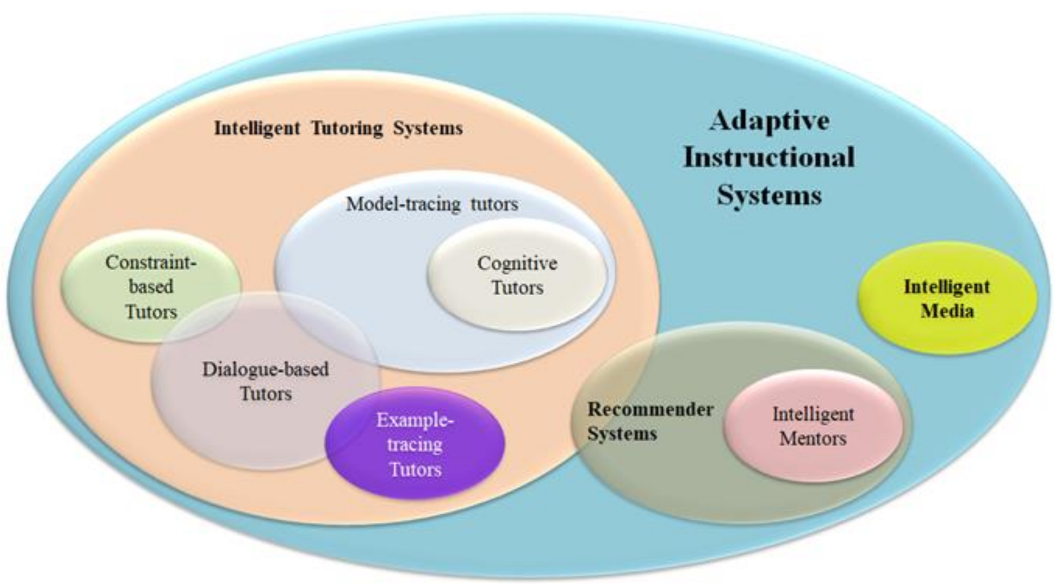

Figure 1. Categories of Adaptive Instructional Systems

Military Need for Adaptive Instruction

Adaptive instruction is a highly desired technology for military training and education. Adaptive instruction has the potential to reduce training costs while enhancing both performance and efficiency. Adaptive instruction has proven to be more effective and efficient than traditional classroom experiences (VanLehn, 2011; VanLehn, et al., 2005; Lesgold, Lajoie, Bunzo & Eggan, 1988) or non-adaptive simulation-based training experiences (Goldberg, Amburn, Brawner & Westphal, 2014). The goal for adaptive instruction is to improve training efficiency (accelerate learning) by intelligently focusing tutoring resources where they are needed most - on gaps in learner knowledge and skill in the context of domain competency goals and near-term learning objectives. Both the US Army Synthetic Training

Environment (STE) and US My Navy Learning (MNL) programs have design goals to enable adaptive instruction within their future training infrastructure, and research is ongoing to enhance AIS capabilities and processes to support practical, affordable implementations. Adaptive instruction is critical element of the Total Learning Architecture sponsored by the Office of Secretary of Defense's Advanced Distributed Learning Initiative. From 2013-2017, NATO also sponsored a multi-national research task group to explore opportunities to exploit ITS technologies for adaptive training in NATO countries (Sottilare et al, 2018).

Today, however, the military has many training systems developed by a variety of vendors that can exchange simulation data under interoperability standards such as the Distributed Interactive Simulation (DIS IEEE 1278) and the High Level Architecture (HLA IEEE 1516). While these standards enable increased trainee immersion in shared synthetic environments, they do not support instructional adaptivity or tailored training in any standardized fashion. The challenges involved in providing adaptive instruction to the military at scale are many and significant (Sottilare, 2018). While adaptive instruction has been a research topic for many years, it has only recently become feasible to meet some of the challenges which previously prevented adaptive instruction from becoming both a practical and cost-effective solution.

RESEARCH AND DEVELOPMENT CHALLENGES

Sottilare (2018) identified eight major challenges associated with bringing adaptive instructional technology from state-of-the-art to state-of-practice. We adapted/expanded this list to account for emerging AIS needs:

1. Common conceptual model of AISs, and their components, functions, and processes
2. Standards for component interoperability to promote reuse and reduce authoring costs
3. Recommended practices to evaluate the efficiency and effectiveness of AISs
4. Efficient (largely automated) authoring processes to create adaptive instruction and curate content in a wide variety of military and non-military task domains
5. Effective/efficient modeling of individual learners, teams, and teams of teams as a basis for real-time tailoring decisions
6. Methods to enable AISs to make optimal instructional decisions: recommendations, strategies (plans) and tactics (actions)
7. Ability to represent team/collective instructional domains for adaptive instruction
8. Ability to build rapport and engagement with learners on both a near-term and career basis
9. Ability to support adaptive distributed/mobile learning

Each of these challenges enumerated above is critical in providing a fully functioning AIS. However, in this section we chose to focus on those challenges (#1, 2, and 3) that directly affect our ability to develop an interoperable, extensible AIS architecture. A major design goal of this emerging AIS architecture is compatibility with current and future training technology (e.g., live and synthetic training simulations, simulators/stimulators, and serious games) in order to minimize disruption to military training pipelines and make AIS solutions affordable.

Developing a Common AIS Conceptual Model

Conceptual models are an abstract representation of common objects or phenomena within a system. They are used to represent a set of ideas which illustrates how the system works or is intended to work. The goals for developing an AIS conceptual model are to:

- Enhance our shared understanding of the scope of AISs (what they are and <u>are not</u>), and how they function
- Promote an efficient method to convey AIS design principles to the public (e.g., users, designers, instructors)
- Provide a reference model for AIS designers to identify system specifications
- Document an AIS framework for future reference

AIS common components include models of the domain, the learner, the instruction, and the user interface (Sottilare, Graesser, Hu & Sinatra, 2018; Sottilare & Salas, 2018; Sottilare & Sinatra, 2018). In our pursuit of a common AIS conceptual model, we are not necessarily requiring each of these models to function the same, but we do wish to understand what functions are essential to this category called AISs. What functions must be common, similar or are allowed to be different? There exist common AIS frameworks in which design principles and processes are consistent within each framework. The Cognitive Tutor (Ritter, Anderson, Koedinger & Corbett, 2007) and its associated authoring processes is one example of an AIS framework with consistent processes and data structures. Another is the Generalized Intelligent Framework for Tutoring (GIFT; Sottilare, Brawner, Goldberg & Holden, 2012; Sottilare, Brawner, Sinatra & Johnston, 2017), but its design principles, processes, and data structures – while consistent – are very different than those of the Cognitive Tutor.

Within the Institute of Electrical and Electronics Engineers (IEEE) Standards Association is an effort to develop an AIS conceptual model standard. This standard (IEEE Project 2247) is intended to define and classify the components and functionality of adaptive instructional systems (AIS). This standard also defines parameters used to describe AISs and establishes requirements and guidance for the use and measurement of these parameters. The purpose of this standard is to enable producers of AISs to describe the overall operation of an AIS; to specify its approach, method, and level of adaptation; and to identify the methods used to implement specific components and interfaces.

Developing an AIS Interoperability Standard

Interoperability is defined as "the ability of two or more software components to cooperate despite differences in language, interface, and execution platform. It is a scalable form of reusability…" (Wegner, 1996). When examining interoperability as an AIS design goal, we are attempting to design interfaces that are defined to a degree that allows information to be exchanged with and understood by other AIS systems or AIS system components (Sottilare & Brawner, 2018). According to Ouksel & Sheth (1999) and Euzenat (2001), interoperability occurs at two levels: syntactic and semantic. Syntactic Interoperability occurs when two or more systems are able to communicate by exchanging data. Syntactic interoperability is a prerequisite for semantic interoperability which occurs when the data exchanged between two or more systems is understandable to each system and can be used by each systems processes.

In the current marketplace, AIS models vary in function and data structure from system to system, domain to domain, and one framework to another. For example, a domain model for an algebra course developed within the Cognitive Tutor framework is not interoperable with, nor directly usable by the GIFT architecture. This limits the ability to reuse components and makes each AIS development unique. This drives costs into the unaffordable range. If we think of current AIS components (learner, domain, instructional, and user interface models) as having unique processes and data structure, how might we insure interoperability without impeding creativity or violating intellectual property rights? To this end, we might examine the information content and formats of the messages exchanged by AIS components as a target for standardization.

Again, under the auspices of IEEE Project 2247, there is activity to develop a data standard to serve as a reference for technical standards that support the exchange of data among AISs and between AISs and other education and training systems. This standard will define the data and data structures to be used in these interactions and exchanges and parameters used to describe and measure them. It will establish requirements and guidance for the use and measurement of the data, data structures, and parameters. The goal of this standard is to provide both syntactic and semantic interoperability.

In pursuing a data standard, the inter-component and inter-system message sets can reflect the changing needs of AIS designers and developers without imposing a standard that could limit creativity and suppress the entry of technology purveyors into the AIS marketplace. This means that we will likely see higher numbers of AIS technology solutions, increased competition, and lower costs to develop AIS solutions.

Developing AIS Recommended Practices for Evaluation

AISs are increasingly being deployed in commercial and open-source versions. These systems have demonstrated the potential to significantly improve learning across many sectors of training and education (Defalco et al, 2017; Goldberg et al 2014; Graesser, Hu, Nye & Sottilare, 2016), but the ability/criteria to evaluate the effectiveness of any individual AIS may not be supported by rigorous scientific methods. While many factors contribute to the design and engineering of an AIS, there significant variation in the features contributing to the adaptivity (automated tailoring) of AISs and the methods instructors and end-users may deploy these systems.

Again, under the auspices of IEEE Project 2247, there is an effort to identify recommended practices for the evaluation of AISs and adaptive instructional technologies. The purpose of this IEEE recommended practice for AISs is to establish criteria and best practices for evaluation of AISs so that consumers can determine the likelihood of desired learning outcomes and program impacts based on the features included in the AIS and the intended usage frequency of those AIS features. Next, we discuss AISs functions and process during pre-instructional, real-time instructional, and post-instructional processes.

HOW ADAPTIVE INSTRUCTIONAL SYSTEMS WORK

To understand how AISs work, we begin by discussing the interaction between the AIS, the learner, and the training system environment (Figure 2). The AIS monitors both the training system environment and the learner with respect to the learning objectives and associated measures, and then adapts inputs based on the condition of the learner and the context of the instruction.

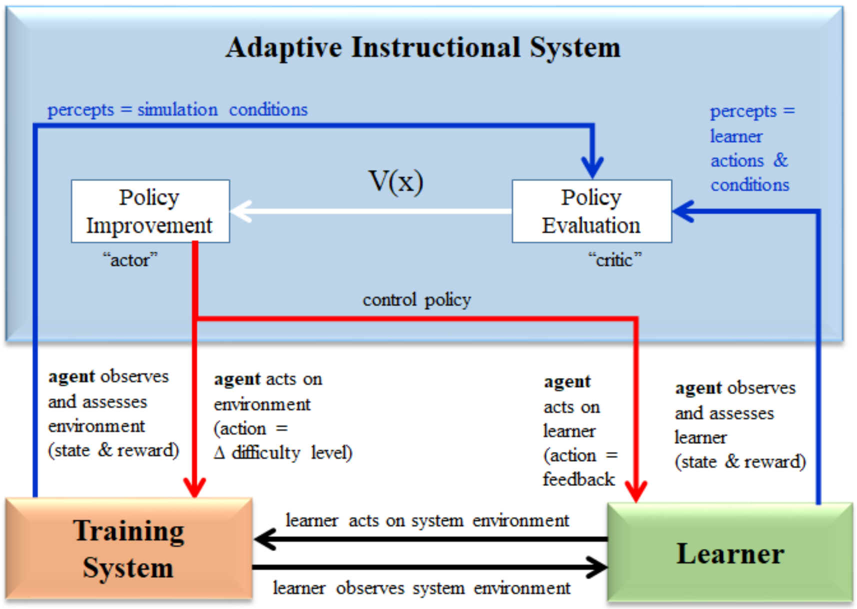

Figure 2. A model of a real-time Adaptive Instructional System (AIS)

In existing military simulation architectures, an individual learner (or team) interacts with a training system scenario (usually a series of events) that is intended to provide an experience that will allow the learner(s) to exercise their knowledge and skills with the goal of learning, or potentially refreshing learning of, a task. In Figure 2, this is illustrated by the interaction between the learner (green box) and the training system (orange box) where the learner acts on the environment and then observes how the environment changes or responds based on that interaction. In an existing military simulation, there is also an instructor function that monitors the learner's progress toward learning objectives. There might also be some adaptation based on the progress of the learner towards learning objectives. This adaptation could be hard coded into the simulation or it could be scenario-driven where the human course manager or battlemaster selects/changes a scenario based on some understanding of the learner's proficiency in the domain under instruction, but there is no formal learner model. In the following sections, we discuss the AIS architectural elements that support learner-centric design, self-improvement or reinforcement learning, interaction between the learner and the AIS, and a variety of AIS processes for initializing AISs, automating instructional management, and evaluating the effectiveness of AISs.

AIS Learner-Centric Design

In an AIS, the learner model is initially populated from historical sources – such as a learning record store or other repository – where learner data can be used to construct a model of the learner's proficiency in the domain to be instructed. During adaptive instruction, the AIS uses data from the training system environment, the learner model and any real-time information sources (e.g., sensor data, assessments or learner inputs) to make instructional decisions (e.g., provide feedback, provide support or change the difficulty of the training scenario). A driving force for adaptation decisions for any individual learner is to keep the learner engaged and challenged, optimizing learning during adaptive instruction. Vygotsky (1978) provides a model of this interaction in his *zone of proximal development* (ZPD) where the difficulty level is managed by the instructor to be compatible with the learner's capabilities. Scenarios that are too easy result in learner boredom and those that are too difficult result in anxiety or withdrawal.

AISs as Self Improving Systems

Another important element of AIS design as shown in Figure 2 is the concept of AISs as self-improving systems through *reinforcement learning* (RL). RL is an area of machine learning where software agents take actions in an environment with the goal of maximizing cumulative reward (Sutton & Barto, 1998). In the case of AISs, we are attempting to optimize learning by capturing the conditions of the learner and the training system environment when the instructional agent makes a decision, and then examining the actual outcome to determine the value of the decision. The more experience the agent has in making decisions, the better those decisions will be over time. For example, a self-improving system could use learner data to consistently update and improve the learner model. This not only allows for a more accurate model of learner interaction, but can also help the AIS to make better decisions for that learner and maintain the interaction within the ZPD. This is illustrated (Figure 2) by policies that are formulated and improved over time through constant evaluation. Both the effectiveness of the selection of the policy to be applied and the implementation of the policy itself are objectives for improvement. In the absence of large datasets, this RL process might be bootstrapped (initialized) to be more effective at the onset of a course of instruction by: 1) implementing policies derived from the literature that are generalizable across domains, and 2) examining norms in specific populations by maintaining population models (Hu & Sottilare, 2019).

AIS-Learner Interaction Loops

To understand how AISs work, we begin by discussing inner loop and outer loop interactions in ITSs, a type of AIS and representative of the largest AIS category (Figure 1). VanLehn (2006) defined inner loop activities by an intelligent tutoring system (ITS) as *step-by step guidance within a problem being worked by a learner during instruction*. "Systems that lack an inner loop are generally called computer-aided instruction (CAI), computer-based training (CBT) or web-based homework (WBH). Systems that do have an inner loop are called [ITSs]" (VanLehn, 2006, p. 233). This inner loop activity is what makes ITSs and thereby AISs adaptive.

We expanded VanLehn's definition of inner loop to include not just problems, but any scenario (or event) in which a learner interacts with media with the goal of learning to do a task. While VanLehn is also specific about step-by-step guidance, we have adopted a more liberal approach in which the interaction between the learner and the tutor: *inner loop activities include any interaction (e.g., guidance, feedback, support) between the AIS and the learner within a scenario, event or problem*. This expanded definition does not preclude the step-by-step approach advocated by VanLehn, but does allow for other AIS-learner interactions and adaptations within the inner loop. Again, building upon VanLehn's work, we define outer loop activities to include any recommendation (*e.g.*, next problem to select, next course to take) made to the learner that is outside of the current scenario, event or problem. These outer loop recommendations often consist of activities related, either directly or indirectly, to the current scenario.

APPLYING ADAPTIVE INSTRUCTION TO MILITARY TRAINING

In applying adaptive instruction to existing training simulations, platform simulators (e.g., aircraft simulators), and serious games, we have considered architectural aspects such as common components, interoperability, and recommended practices for evaluating AISs. Of the three architectural challenges previously discussed in this paper, interoperability provides the greatest challenge and greatest payoff. Therefore, we considered applications of adaptive instructional technology to existing/future military training systems under the lens of interoperability. Two likely approaches to adapting existing simulation architectures to enhance tailored instruction are presented below.

Approach #1: Stimulating Military Training Systems with Adaptive Instructional Systems

Our first approach is one in which the adaptive instructional technology is external to the existing simulation architecture and the AIS is used as a stimulator for feedback and instructional decisions implemented in the simulation architecture.

To fully implement this approach of AISs as stimulators for existing/future training systems, we begin to examine details about the data exchanged between AIS common components (Figure 3, blue boxes), the learner (Figure 3, green box) and a training environment (Figure 3, orange box). In this stimulator approach, the AIS is external to the training environment and the data shared between the composite system (AIS, learner and training environment) is shown in Figure 3 as yellow boxes. Standardizing these messages will allow both composite subsystem and AIS component interoperability.

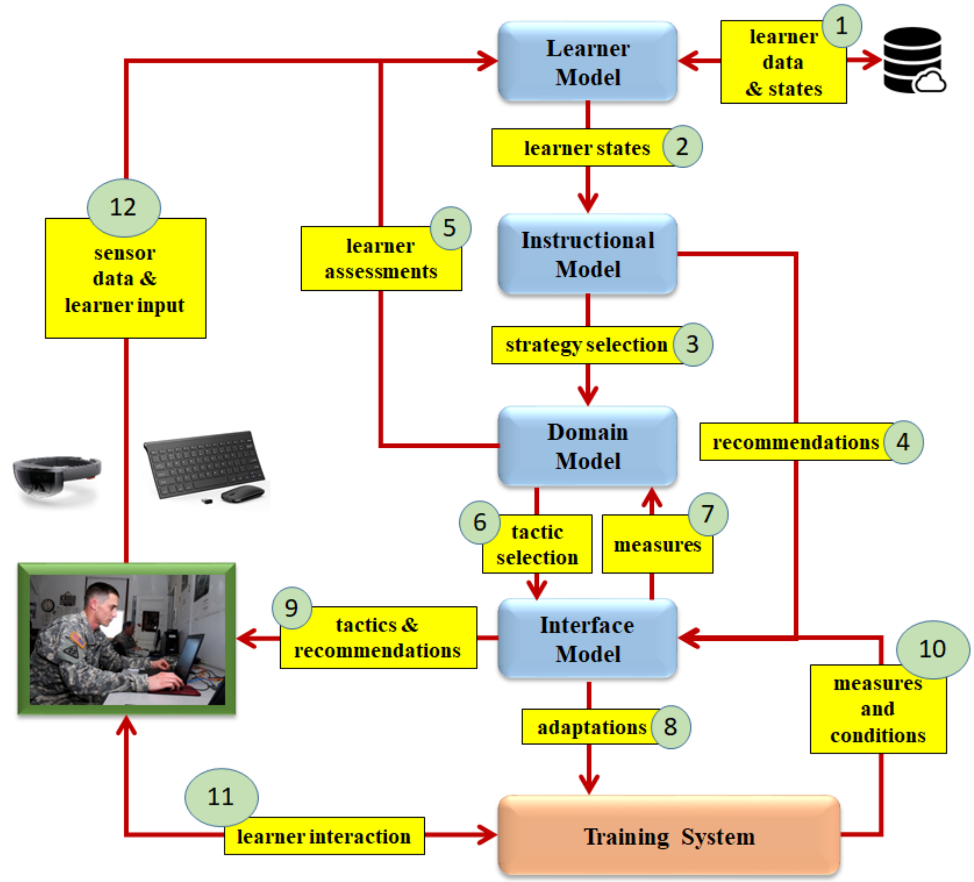

Figure 3. Using an AIS as a Real-time Stimulator for Military Training

To support the stimulator approach, the following types of messages (numbered and shown in yellow in Figure 4) are required:

1. Learner State/Trait Initialization – this message type allows the AIS to pull relevant learner states from a repository (cloud or local) to initialize the AIS learner model; examples of learner state initialization messages might include the learner's proficiency for the domain to be instructed or the learner's personality traits which are fairly steady-state in adult learners
2. Learner States Updates – these messages include learning, performance, domain proficiency, and affect (emotions, mood, and personality) states along with others, and are derived from data sourced by domain model (learner assessments), historical data (learner records in the repository), sensor data (physiological and behavioral) and learner input
3. Strategy Selection – as part of instructional process, AISs assess learner states and appropriate select strategies (plans for action) based on reinforcement machine learning models and/or recommended practices in the literature; strategy selections could include, but are not limited to: ask a question, prompt the learner for more information, ask the learner to reflect on a recent experience, change the difficulty level of the training environment, give the learner feedback or direction or provide the learner with a hint
4. Recommendations – as part of the instructional process, AISs may also provide recommendations to the learner about what they should do next; recommendations could include: take a break, skip this problem and

move to another problem, take a specific course after completing the one they are in or remediate by going back to review previous material; recommendations are relayed directly to the interface model and then to the learner without the need for a tactical selection

5. Learner Assessments – whether they are tests or in-situ exercises where the learner can apply knowledge and skill, the results of learner assessments are transferred from the domain model to learner model where they are used to re-evaluate the learner's proficiency in the current domain of instruction; assessments typically focus on the recall of knowledge and/or the application of skill
6. Tactic Selection – in AIS architectures such as GIFT, the domain model uses the strategy selection to narrow the tactical action; for example, if the strategy is to ask the learner a question, then the tactic is to select an appropriate question (from a question bank) that is relevant to the instructional context (where the learner is in the instruction)
7. Measures – the learning objectives, the training environment and the scenario(s) being used in the instruction will drive the measures needed to assess the learner's progress toward the learning objectives; measures are defined in the interface model as part of the integration process for linking the AIS with the training environment
8. Adaptations – this message is used to drive changes in the training environment and is the action taken in response to both strategy and tactic selection; this message contains information about the most recent instructional decision and how that decision affects the current scenario
9. Tactic and Recommendation Presentation – the focus of this message is to provide the interaction with the learner required by the strategy and/or tactic selection; while technically, tactic presentation to the learner is also an adaptation, we distinguish it from adaptation directed at the training environment since the message content will be very different; recommendations do not require a tactic selection
10. Measures and Conditions – the information on measures is pulled directly from the training environment based on the interface model definition; the conditions of the instruction are also pulled directly from the training environment through the interface and into the domain model to support assessments
11. Learner Interaction – the learner interacts directly with the training environment and only the relevant measures and conditions are captured to support assessments; no specific learner interaction message is required in this design as it is already captured by the measures and conditions message type
12. Sensor Data and Learner Input – messages acquire data about the learner independent of the training environment and this data is used by the learner model to assess learner states of various kinds

Using this stimulation approach will permit AISs that meet the standards identified previously in this paper to interact with and drive instructional adaptations in existing and future military training systems through simple interface models (e.g., gateways). AIS architectures such as GIFT have already proven gateways to be an effective means to support adaptive instruction for:

- Serious games
    - Virtual Battle Space to train dismounted infantry tasks (Goldberg et al, 2012)
    - VMedic to support tactical combat casualty care task training (DeFalco et al, 2017)
- Virtual simulations
    - Dynamic Environment Testbed used to train excavator tasks (GIFT, 2014)
- Live simulations and real equipment
    - USMA land navigation course used to teach map reading and terrain recognition (Sottilare & LaViola, 2015)
    - Medical triage training (Sottilare, Hackett, Pike & LaViola, 2016)
    - Encryption Gear
- Educational platforms
    - edX used to teach educational data mining techniques (Aleven et al, 2018)
- Problem-Solving platforms
    - Sudoku puzzles (Holden & Sottilare, 2015)
    - Logic puzzles (Sinatra, Sims & Sottilare, 2014)

Approach #2: Embedding Adaptive Instructional Systems in Existing Military Training Systems

Next we examine an alternate approach to integrating AISs using gateways to stimulate military training systems. This approach embeds the instructional loops shown in Figure 4 into a military simulation architecture to provide more "native" adaptive instruction. In most cases, the message types and associated formats can remain the same as they are in our stimulator approach (Approach #1). The primary difference is the direct interaction between the AIS functions and the simulation manager functions within the military training system. This could require changes to the adaptation messages to match the form and function of native simulation manager inputs.

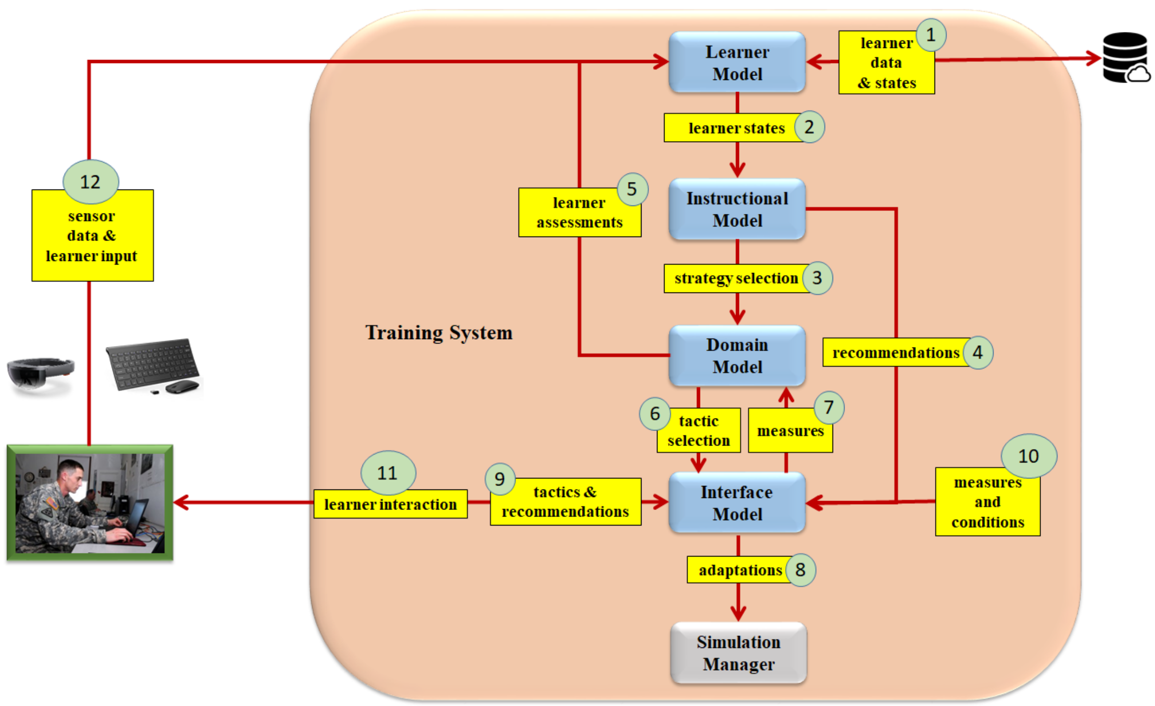

Figure 4. Embedding AIS functions in Military Training Environments

An example of an embedded approach is adaptive marksmanship. A prototype adaptive instructional capability was developed for the US Army's engagement skills training simulation (Goldberg, Amburn, Brawner & Westphal, 2014). The inner and outer loops of the adaptive instruction were created as a single module and integrated into the software baseline of the emerging engagement skills trainer. While on the surface the embedded approach would appear to be more work, it is of the similar magnitude as the AIS stimulator approach. Protocols exchanged between components can easily be tailored or streamlined to meet new requirements, and changes in any simulation scenario measures could be easily mapped to the interface model. The advantage of this approach is in its efficiency as there is no excess messaging or data required. Only the information needed to support native assessments is required to be mapped to the interface model. The disadvantage of the embedded approach is that portions of this solution may not easily transfer to other military training simulations.

NEXT STEPS

Recommended next steps to make AISs practical for military training are:

- Develop a standard AIS conceptual model as a basis for identifying AIS components, processes, and data exchange needs
- Develop standards for AIS interoperability to support data exchange between common AIS components described in the AIS conceptual model
- Incentivize the AIS marketplace to produce much needed AIS prototype architectures to support both stimulator and embedded modes
- Develop recommended practices for evaluating the capabilities of new AIS technologies (tools and methods)
- Build standards and recommended practices for new AIS architectures upon already proven design principles in AIS architectures such as GIFT and the Cognitive Tutor

- Incentivize the AIS marketplace to enhance authoring, deployment, instructional management, and evaluation processes to further improve the cost/benefit associated with AISs

A FINAL WORD

An important caution moving forward is that AISs are not a panacea for military training. It is important to understand the contributions of clear learning objectives, good/relevant content, and good measures to learning and performance outcomes. While AISs are learner-centric technologies that offer effective strategies and tactics for tailoring training, they must have clear objectives that can be measured and content/scenarios that are relevant to those objectives in order to optimize their effectiveness. Making AISs affordable and practical options for computer-based instruction will hasten their widespread use in military training, but this is contingent upon continued reports of their effectiveness in a variety of domains required by military organizations. "Even though we have conducted over four decades of ITS research and shown ITSs to be effective tools in providing one-to-one-tutoring, ITSs are not ubiquitous. In large measure, the skills needed to author an ITS and the cost of those skills limit ITS use. Even a simple ITS providing one hour of instruction may take 200 hours to develop at a cost of $50,000. This cost may not be practical for low density or low throughput courses" (Fletcher & Sottilare, 2014), but may be very affordable for widely taught courses (e.g., combat lifesaver skills that are taught to every soldier).

There is more to consider than just cost. Costs and benefits are usually measured in terms of funding, but other measures (e.g., productivity, operational effectiveness, health, quality of life, morale, and human life) are also variables of interest in determining the benefit of AIS technology applied to the military training domain. The widespread use of AISs in the future is also contingent upon a proven return-on-investment (ROI). ROI indicates how many units of net benefits are returned (after investment costs have been subtracted out) per unit of cost. In contrast to current military training systems, AISs require a higher level of investment based on the artificial intelligence that drives their decisions and the greater amount of content required to support options for tailoring. An ROI decision-making framework will be critical to painting an objective picture of the true value of AISs and artificial intelligence will play a significant role in automating AIS processes. As we see greater efficiencies in AIS authoring, deployment, instructional management, and evaluation processes, the costs associated with AIS technologies will shrink and AISs will become an increasingly attractive option for military training.

REFERENCES

Aleven, V., Sewell, J., Popescu, O., Sottilare, R., Long, R., & Baker, R. (2018, June). Towards Adapting to Learners at Scale: Integrating MOOC and Intelligent Tutoring Frameworks. In Proceedings of the *Learning @ Scale Conference*, London, England, June 26-28, 2018.

DeFalco, J., Rowe, J., Paquette, L., Georgoulas-Sherry, V., Brawner, K., Mott, B., Baker, R., & Lester, J. (2017). Detecting and Addressing Frustration in a Serious Game for Military Training. *International Journal of Artificial Intelligence in Education*. DOI: 10.1007/s40593-017-0152-1.

Euzenat J. (2001). Towards a principled approach to semantic interoperability. In Proc. *IJCAI 2001 workshop on ontology and information sharing* 2001 Aug 4 (pp. 19-25).

Fletcher, J. & Sottilare, R. (2014). Cost Analysis for Training & Educational Systems. In R. Sottilare, A. Graesser, X. Hu, & B. Goldberg (Eds.) *Design Recommendations for Intelligent Tutoring Systems: Volume 2 - Instructional Management*. US Army Research Laboratory, Orlando, Florida. ISBN: 978-0-9893923-2-7.

GIFT (2014). Dynamic Environment Testbed. Retrieved from: https://gifttutoring.org/news/37

Goldberg, B., Amburn, C., Brawner, K., & Westphal, M. (2014). Developing models of expert performance for support in an adaptive marksmanship trainer. In Proceedings of the *Interservice/Industry Training, Simulation, and Education Conference*, Orlando, Florida, December 2014.

Goldberg, B., Brawner, K. Sottilare, R., Tarr, R., Billings, D., & Malone, M. (2012). Use of Evidence-based Strategies to Expand Extensibility of Adaptive Tutoring Technologies. In Proceedings of the *Interservice/Industry Training Simulation & Education Conference*, Orlando, Florida, December 2012.

Graesser, A. C., Hu, X., Nye, B., & Sottilare, R. (2016). Intelligent tutoring systems, serious games, and the Generalized Intelligent Framework for Tutoring (GIFT). In H. F. O'Neil, E. L. Baker, and R. S. Perez (Eds.), *Using games and simulation for teaching and assessment* (pp. 58–79). Abingdon, UK: Routledge.

Graesser, A. C., Hu, X., & Sottilare, R. (2018). Intelligent tutoring systems. *International handbook of the learning sciences* (pp. 246-255). Routledge.

Holden, H. & Sottilare, R. (2015, May). What Happens When a Pedagogical Agent's Emotional Support and Competency is Alternated in a Single Learning Task? In Proceedings of the 28th International Conference of the Florida Artificial Intelligence Research Society, Hollywood, Florida, 18-20 May 2015.

Hu, X. & Sottilare, R. (2019, accepted). Using xAPI and Population Models to Support Self-Improving Adaptive Instructional Systems: A framework and conceptual design. *Advanced Distributed Learning iFest*. Office of the Secretary of Defense.

Lesgold, A.M., Lajoie, S., Bunzo, M. & Eggan, G. (1988). Sherlock: A coached practice environment for an electronics trouble shooting job. LRDC Report. Pittsburgh, PA: University of Pittsburgh, Learning Research and Development Center.Ouksel A.M. & Sheth A. (1999). Semantic interoperability in global information systems. *ACM Sig-mod Record.* 1999 Mar 1;28(1):5-12.

Ritter, S., Anderson, J. R., Koedinger, K. R., & Corbett, A. (2007). Cognitive Tutor: Applied research in mathematics education. Psychonomic bulletin & review, 14(2), 249-255.

Sinatra, A., Sims, V. & Sottilare, R. (2014). Technical Report: The Impact of Need for Cognition and Self-Reference on Learning a Deductive Reasoning Skill. *Army Research Laboratory* (ARL-TR-6961), June 2014.

Sottilare, R. & Brawner, K. (2018, June). Component Interaction within the Generalized Intelligent Framework for Tutoring (GIFT) as a Model for Adaptive Instructional System Standards. In the *Adaptive Instructional System (AIS) Standards Workshop of the 14th International Intelligent Tutoring Systems (ITS) Conference*, Montreal, Quebec, Canada.

Sottilare, R.A., Brawner, K.W., Goldberg, B.S. & Holden, H.K. (2012). The Generalized Intelligent Framework for Tutoring (GIFT). Concept paper released as part of GIFT software documentation. Orlando, FL: US Army Research Laboratory – Human Research & Engineering Directorate (ARL-HRED). Retrieved from: https://gifttutoring.org/attachments/152/GIFTDescription_0.pdf

Sottilare, R., Brawner, K., Sinatra, A. & Johnston, J. (2017). An Updated Concept for a Generalized Intelligent Framework for Tutoring (GIFT). Orlando, FL: US Army Research Laboratory. May 2017. DOI: 10.13140/RG.2.2.12941.54244.

Sottilare, R.A., Fletcher, J.D., Skinner, A., Perez, R., Durlach, P., Zotov, V. & Alexander, T. (2018). *NATO Final Report of the Human Factors & Medicine Research Task Group (HFM-RTG-237), Assessment of Intelligent Tutoring System Technologies and Opportunities.* NATO Science & Technology Organization. DOI: 10.14339/STO-TR-HFM-237. ISBN 978-92-837-2091-1.

Sottilare, R., Graesser, A., Hu, X. & Sinatra, A. (2018). Introduction to Team Modeling. *Design Recommendations for Intelligent Tutoring Systems: Volume 6 – Team Tutoring*. Army Research Laboratory, Orlando, Florida. ISBN: 978-0-9977257-4-2.

Sottilare, R., Hackett, M., Pike, W., & LaViola, J. (2016). Adaptive instruction for medical training in the psychomotor domain. *The Journal of Defense Modeling and Simulation: Applications, Methodology, Technology.* https://doi.org/10.1177/1548512916668680.

Sottilare, R. and LaViola, J. (2015, December). Extending Intelligent Tutoring Beyond the Desktop to the Psychomotor Domain: A survey of smart glass technologies. In Proceedings of the *Interservice/Industry Training Simulation & Education Conference*, Orlando, Florida, December 2015.

Sottilare, R. & Salas, E. (2018). Examining Approaches to Building Intelligent Tutoring Systems for Teams. *Building Intelligent Tutoring Systems for Teams: What Matters*. Emerald Publishing, Bingley, United Kingdom.

Sottilare, R. & Sinatra, A. (2018). Considerations in the Design of a Framework to Support Team Tutoring. *Building Intelligent Tutoring Systems for Teams: What Matters*. Emerald Publishing, Bingley, United Kingdom.

Sutton, R. S., & Barto, A. G. (1998). *Introduction to reinforcement learning* (Vol. 135). Cambridge: MIT press.

VanLehn, K. (2006). The behavior of tutoring systems. International journal of artificial intelligence in education, 16(3), 227-265.

VanLehn, K., Lynch, C., Schulze, K., Shapiro, J. A., Shelby, R., Taylor, L., et al., (2005). The Andes physics tutoring system: Lessons learned. *International Journal of Artificial Intelligence and Education*, 15(3), 147–204.

VanLehn, K. (2011): The Relative Effectiveness of Human Tutoring, Intelligent Tutoring Systems, and Other Tutoring Systems, *Educational Psychologist*, 46:4, 197-221

Vygotsky, L.S. (1978). Mind in Society. Cambridge, MA: Harvard University Press.

Wegner, P. (1996). Interoperability. ACM Computing Surveys (CSUR), 28(1), 285-287.