DOMAIN MODELING IN SUPPORT OF ADAPTIVE INSTRUCTIONAL DECISIONS IN THE GENERALIZED INTELLIGENT FRAMEWORK FOR TUTORING

Robert A. Sottilare[(a)], Scott J. Ososky[(b)] and Michael W. Boyce[(c)]

[(a, b, c)]U.S. Army Research Laboratory and [(b, c)]Oak Ridge Affiliated Universities
[(a)]robert.a.sottilare.civ@mail.mil; [(b)]scott.j.ososky.ctr@mail.mil; [(c)] michael.w.boyce.ctr@mail.mil

ABSTRACT

This paper focuses on aspects of domain modeling for Intelligent Tutoring Systems (ITSs), adaptive training tools to support one-to-one computer-based instruction. Domain modeling represents knowledge for a particular task or concept and includes: domain content (a library of scenarios or problem sets); an expert or ideal student model with measures of success; and a library of tactics or actions (e.g., questions, assessments, prompts, and pumps) which can be taken by the tutor to engage or motivate the learner and optimize learning. Today, ITSs support well-defined domains in mathematics, physics, and software programming. Since the military often operates in complex, dynamic, and ill-defined domains, it is necessary to expand the scope of domain modeling. We examined domain knowledge representation across a variety of dimensions: task domains, complexity, definition, and physical interaction modes in order to understand instructional options and drive adaptive training decisions.

Keywords: adaptive training, domain modeling, intelligent tutoring systems

1. INTRODUCTION

ITSs have been applied in well-defined, cognitive domains which include mathematics, physics, chemistry, and software programming languages. The future holds more challenging domains for ITSs which include military instruction. We envision the use of ITSs to drive and adapt military instruction in existing military simulations (see Figure 1).

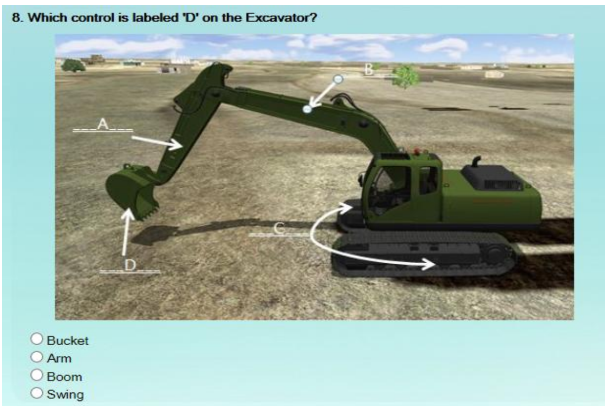

Figure 1: Military Construction Equipment Training

Military instruction is in many cases more challenging due to the large degrees of freedom encounter by learners during training. For example, learners in serious games have a large number of options with respect to actions available. This raises the complexity of these training and education environments compared to more process-oriented domains. Another level of complexity is encountered in modeling teams of learners as most military tasks also involve collaborative roles.

To dissect this problem of domain complexity in adaptive instruction, we should address how ITSs function and illustrate their decisions with respect to learners and training environments. ITSs are composed of four typical models: a learner or trainee model, an instructional or pedagogical model, a domain model, and a communication model (user interface). The domain model typically includes an expert or ideal student model by which the ITS measures, compares and contrasts the progress of the learner toward learning objectives. The domain model also includes the training environment, the training task and all of the associated instructional actions (e.g., feedback, questions, hints, pumps, and prompts) which could possibly be delivered by the adaptive system for that particular training domain. Adaptive training system agents observe changes in the learner's states (e.g., workload, engagement, performance and emotions) and respond through interactions with the learner (e.g., feedback, direction, support) or changes to the training environment (e.g., increase or decrease problem or scenario challenge level to match the learner's state or domain competency) as shown in Figure 2.

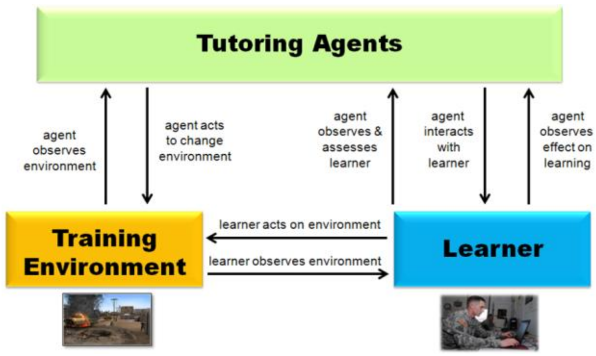

Figure 2: Adaptive Interaction between Learners, Training Environments and Tutoring Agents

This interaction is an essential design element in the Generalized Intelligent Framework for Tutoring (GIFT; Sottilare, 2012; Sottilare, Brawner, Goldberg, and Holden, 2012; Sottilare, Holden, Goldberg, and Brawner, 2013), an open-source architecture (tools, methods, ontology) for: authoring ITSs; managing instruction during adaptive training experiences; and evaluating the effect on learning, performance, retention, and transfer.

2. DIMENSIONS OF DOMAIN MODELING

Domain knowledge may be represented across a variety of dimensions: task domains (cognitive, affective, psychomotor, social, and hybrid domains); task complexity (simple, compound or multifaceted tasks); task definition (well-defined, ill-defined or unknown measures of success), and physical interaction modes (static, limited dynamics, enhanced dynamics, and full dynamics also known). Our goal was to understand how to represent domains so GIFT could optimally select tactics (actions by the tutor) based on the optimal selection of strategies (plans for action grounded in instructional theory) and instructional context determined by the domain model as shown in the updated learning effect model (Figure 3).

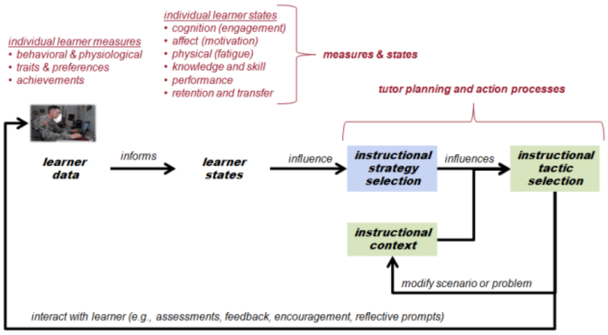

Figure 3: Individual Learning Effect Model (Sottilare, Sinatra, Boyce, and Graesser, 2015)

2.1. Task Domains for Adaptive Training Systems

First, we examine representations of task domains: cognitive (Bloom and Krathwohl, 1956), affective (Krathwohl, Bloom, and Masia, 1964), psychomotor (Simpson, 1972), and social (Soller, 2001). Understanding the dimensions of these domains can facilitate identification of critical learning and performance measures and reduce the burden of authoring adaptive training systems.

2.1.1. Modeling the Cognitive Domain

Sometimes called the *thinking* domain, tasks in this domain stress the learner's thinking capacity (workload management), problem-solving capability, decision-making, and focus or engagement. 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, visual and spatial processing, 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*- the learner's ability to recall information, *understanding*– the learner's ability to organize, compare, and interpret information, *applying*- the learner's ability to use information to solve problems, *analyzing*- the learner's ability to examine information and make inferences from that information, *evaluation*- the learner's ability to use information to make optimal judgments, and *creating*- learner's ability to build new models (e.g., plans) from information.

Most of the ITSs in existence today focus on this task domain. Examples include model-tracing (also called example tracing) tutors which use a set of steps to walk the learner through the process of solving a problem. Mathematics, physics, and software programming are the most common types of model-tracing tutors. These domains constitute simple procedural tasks.

Matthews (2014) notes organizations generally do a good job of training relatively simple skills. However, a more challenging goal is to teach higher order cognitive skills such as decision-making and judgment. The military has large investments in partial-task and scenario-based training systems which use relatively fixed processes to guide the learner based primarily on individual and team performance measures. A concern with these systems is that military personnel learn how to win within the constraints of the system but the effect on learning, retention, and transfer is not well understood. Research is needed to build adaptiveness into these training systems and thereby optimize deep learning. A goal of this research is to reduce the time to competency to allow time for over-training and deeper learning experiences which transfer more efficiently to the operational environment. As the often cited paper on transfer of training (Baldwin & Ford, 1988) discusses, transfer occurs through more than repeated practice, rather it is providing opportunities through differing views and representations of content, for the mental abstraction which provides the cognitive connection needed to move from training to operational contexts.

2.1.2. Modeling the Affective Domain

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

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

Very little training (outside of classroom-based training) is currently provided to exercise/grow skills in this important task domain and almost no adaptive training has been created to support this domain. Research is needed to understand measures for this task domain, developing low-cost methods to determine the learner's affective state (Carroll, Kokini, Champney, Fuchs, Sottilare & Goldberg, 2011), and any unique characteristics required in authoring affective domain scenarios (Sottilare, 2009).

2.1.3. Modeling the Psychomotor Domain

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

While this domain is well represented in military training, research is needed to build adaptiveness into these training systems and thereby optimize deep learning. A goal of this research is to reduce the time to competency to allow time for over-training and deeper learning experiences which transfer to the operational environment.

2.1.4. Modeling the Social Domain

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

However, it is not as simple as adding up the performance of each individual team member to find the performance of the team. Feedback which is appropriate for an individual team member may be inappropriate to be broadcast to the whole team. For this reason, we are developing models within GIFT at both the individual and team level as shown in Figure 4.

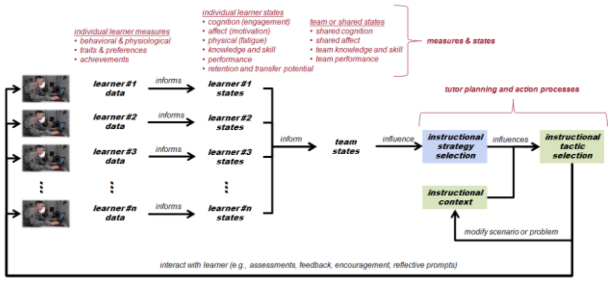

Figure 4: Team Learning Effect Model (Sottilare, Sinatra, Boyce, and Graesser, 2015)

2.2. Task Complexity and Adaptive Instruction

Next, we examine representations of task complexity for domain modeling. Task complexity refers to the level of challenge and the range of difficulty in understanding and performing the task. Task complexity can range from simple procedural tasks to more complex multifaceted tasks. Task complexity is important in accessing the near-term performance of the learner during adaptive training experiences. Referring back to the Individual Learning Effect Model in Figure 2, it is easy to see that the ITS's instructional options fall primarily into two categories of tactics or actions based on Vygotsky's Zone of Proximal Development (ZPD; 1978): interact with the learner to assess their performance, provide feedback or encouragement, or engage them in a reflective discourse; or modify the problem or scenario to more closely match the capabilities (knowledge and skill) of the learner.

Understanding task complexity along with learner capabilities is essential in supporting adaptive instructional decisions. Per the ZPD (Vygotsky, 1978), when the learner's level of domain competency does not match the complexity of the task, the learner is either bored when the task is too easy or anxious (stressed) when the task is too difficult. If the learner is bored, instructional options in adaptive training systems include increasing the complexity of the problem or scenario or reducing the amount of scaffolding or support provided by the ITS. If the learner is anxious, the instructional options are to reduce the complexity of the problem or scenario or increase the amount of scaffolding or support.

2.3. Task Definition and Adaptive Instruction

Variable task definition refers to how well the domains are understood in terms of measures of performance. Measures of performance are typically most effective when the problem space has clear boundaries / constraints and is well-defined. Well-defined domains (e.g., mathematics) typically have one correct path to a successful outcome and a set of specific measures of success. Ill-defined domains (e.g., leadership) may have multiple paths to successful outcomes, and tend to have less defined measures of success. The representation of task definition in adaptive training systems is essential to understanding measures of success.

Human Factors Engineering (HFE) has developed techniques to assist in further defining this domain. Work Domain Analysis (WDA) models a system in terms of the environmental, physical, or social constraints placed on a user (Naikar, 2013). In ITSs, this would be the composition of the goals of the system, the rules which underlie those goals, and how those constraints are represented to the learner. The second step to WDA is to break down the system in terms of requirements, which is specifically applicable to an ITS architecture (e.g., GIFT). Called an abstraction-decomposition matrix, each level of constraints is broken down according to subsystems to provide as understanding of performance at every level. From there, a Hierarchical Task Analysis (HTA; for a review see Stanton, 2006) can analyze the domain and break it down into a series of plans which are composed of tasks and subtasks to help understand and develop success criteria.

Today, ITSs which support well-defined task domains use specific measures to compare and contrast learner performance to an expert model or minimum standard. While it may not be possible to define specific measures for ill-defined domains, it may be possible to define constraints or policies which must be followed by the learner. The WDA combined with the HTA can help to clarify those relationships and provide key concepts that the learning instruction must include. A deviation from a successful path to an unsuccessful path results in initiation of action by the ITS.

2.4. Physical Interaction and Adaptive Instruction

Finally, we examine modes of dynamic interaction. Modeling the type and degree of physical interaction may impact transfer or the degree to which knowledge and skills developed in training are used in the operational environment. Although physical interaction via tangible user interfaces has received a lot of interest both in the commercial and classroom environment, empirical research on the impact of learning outcomes is sparse. The terms *intuitive*, *collaboration* and *engagement* are often mentioned, but the supporting data is missing. However studies performed at Stanford University have begun to show progress on the effects of learning (Schneider, Jermann, Zufferey, & Dillenbourg, 2011; Schneider, Wallace, Blikstein, & Pea, 2013).

Further supporting the role of tangible interfaces in learning, in a recent review on the impact of effect of manipulatives on learning, Pouw, van Gog, and Paas (2014), challenge two of the common perceptions of physical interaction and learning: 1. physical interactions, due to their richness, impose a higher cognitive load, and 2. transfer of learning involves a change from concrete representation to symbolic, negatively influencing learning. They respond to these views arguing for terms that they called embedded and embodied cognition. For embedded, they claim that in certain situations the added richness can alleviate cognitive load by embedding the learning cognitive activity into the environment. For embodied they argue that instead of changing the representation from concrete to symbolic, working with manipulatives involves the use of sensorimotor processes that draw on the perceptual and information rich nature of the interaction.

The representation of this embodied cognition depends on the type of physical interaction and how it engages both the perceptual and motor systems of the user. We have defined four levels of physical interaction in support of adaptive training: static, limited kinetic, enhanced kinetic, and full kinetic.

Static training environments (e.g., desktop computer training) allow the learner to perform primarily cognitive tasks (e.g., decision-making and problem solving). Limited kinetic tasks allow for full gestures, and limited motion in a restricted area. Movement and tracking of the learner from standing positions to kneeling, sitting or supine positions is supported so the range of physical tasks is broader than in static tasks.

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

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

Full dynamic mode transfers tutoring to the operational environments and could also be called embedded training or in-the-wild training. Full dynamic mode is critical to support tasks where a very high degree freedom of movement and a high degree of interaction with other learners are critical to learning, retention, and transfer to the operational environment.

It is anticipated that psychomotor and social tasks may be best taught in full dynamic mode or an environment more closely resembling the operational environment. Research has shown that retrieval of learned information is better when the original learning context is reinstated during task performance and that contextual dependencies also extend to perceptual-motor behavior (Ruitenberg, De Kleine, Van der Lubbe, Verwey, and Abrahamse, 2012). This supports the notion that a misalignment between physical dynamics in training tasks will slow transfer of psychomotor skills during operations, and that a better alignment of the physical aspects of training tasks with how they will be performed on the job will result in more efficient transfer of motor skills.

3. IMPLICATIONS FOR PRACTICE

The progress that has been made in domain modeling, along with current research needs, does not exist in isolation with respect to ITS development. Understanding that the domain model is one of four core ITS models along with the pedagogical, learner, and communication models, respectively. It is important to recognize that advancing the state of the art within one model will have an influence on the others. For example, establishing measures for the cognitive domain will influence the data structure requirements of the learner model and, in turn, the physical sensors that might be required to populate the model. Likewise, developing adaptive training for psychomotor domains in *full dynamic mode* might require a paradigm shift in configuring the communications module for ubiquitous, natural user interfaces instead of computer interfaces.

The Generalized Intelligent Framework for Tutoring (GIFT; Sottilare, 2013; Sottilare, Sinatra, Boyce & Graesser, 2015) was designed with those aforementioned domain modeling challenges in mind. As the name suggests, GIFT was designed to be domain independent, and therefore generalizable to different domains including associated interaction modalities, performance environments and learner modeling data sources. Additionally, each of the GIFT modules (including Domain and Pedagogical) are separable within the Framework, meaning that different instructional approaches, or domains of instantiation can be implemented within the same framework.

Specifically, the current version of GIFT handles domain representations inside of a Domain Module, configured by an object called a Domain Knowledge File (DKF). With this object, domains can be organized as a series of Tasks, Concepts, and Conditions. The DKF also references or -contains assessment logic for use with a training application, such as a virtual environment application. GIFT uses the DKF configured Domain Module in order to communicate changes in learner states, which may be based on cognitive, affective, or performance data gathered from the learner. The Domain Module can provide responses to micro-adaptive instructional strategies from the pedagogical engine in response to those learner state transitions in the form of feedback and/or training scenario adaptations. DKF files can be reused within GIFT, and new DKF files can be configured via GIFT's authoring tools.

In addition to the domain model and its ITS complements, a number of additional elements support real-world tutoring and are integral to the overall strategy for GIFT. Those elements are *architecture*— the technological backbone of the ITS, *authoring*— the tools and systems that enable the creation of the ITS, and *analysis*— those processes (including experimentation) that serve to evaluate the effectiveness of training system configurations. Creating a more robust domain module in support of military tasks potentially adds complexity to each of these elements. While such complexity may be expected in software engineering or scientific measurement, complexity is a significant threat to *authoring*.

One of the primary goals for GIFT is to reduce the time and skill required to author and assesses adaptive tutors (Sottilare & Gilbert, 2011). However, ITS authoring is an area in which persons with limited programming experience (e.g., instructors, subject matter experts) may be responsible for the creation and management of adaptive tutors. Even the *concept* of authoring an adaptive tutor represents a new content creation activity, the current state of which is characterized by a series of tradeoffs between *usability*, *depth*, and *flexibility* (Murray, 2004). Research will be needed to determine appropriate levels of domain model transparency and the appropriate level of author-control over its configuration.

In an effort to address authoring complexity in GIFT, for example, we are developing GUI-based tools to semi-automate the authoring process. These revised authoring tools are intended to provide usable interfaces to authors without the requirement to write computer code. Through continuous development, we intend to further improve the authoring experience by leveraging best practices in experience design to promote learnability. For instance, authoring templates can be used to increase efficiency, and the progressive disclosure of authoring tool functions / interfaces can help to promote learnability of the authoring system (Lightbown, 2015). Alternatively, advances in ITS *architecture* may eventually enable near full-automation of tutor authoring, though this effort should be viewed as a parallel option to, not a replacement for, user-generated tutors.

The intelligent tutor is a system of interconnected models, supported by elements that enable its functionality. In practice, it is important to consider how advances in the domain module will impact the other system components, and how the demands of complex domains, such as military tasks, impact design and implementation requirements at the system-level.

4. CONCLUSIONS

Many military tasks are hybrids of task domains in that they include aspects of cognitive (thinking – evaluating, problem-solving, and decision-making), affective (feeling – making value judgments), psychomotor (doing – physical action), and/or social (collaborating – working in teams). Military training differs greatly from traditional ITSs which are primarily problem-based (e.g., mathematics, physics, computer programming) and generally vary only in complexity. Given much of military training is scenario-based, the realism of the training environment, accessibility of the training, the complexity of the scenario, the physical dynamics of the task, and the variable level of definition are all design considerations for adaptive training systems for military use. It will be essential to match the attributes of the environment to the task domain by asking the question "what is necessary to train the task effectively". This variability in adaptive training and educational domains will allow for greater opportunities for military personnel to train at the point-of-need and to train more closely to how they fight. This is anticipated to result in greater learning, performance, retention, and transfer of skills to the operational environment.

REFERENCES

Baldwin, T. T., & Ford, J. K. (1988). Transfer of training: A review and directions for future research. Personnel psychology, 41(1), 63-105.

Bloom, B. S., & Krathwohl, D. R. (1956). Taxonomy of educational objectives: The classification of educational goals. Handbook I: Cognitive domain.

Carroll, M. Kokini, C., Champney, R., Fuchs, S., Sottilare, R., & Goldberg, B. (2011). Assessing Trainee States in Intelligent Tutoring Systems: Using Low Cost Sensors for Affective and Cognitive State Modeling. In Proceedings of the *Interservice/Industry Training Simulation & Education Conference*, Orlando, Florida, December 2011.

Krathwohl, D. R., Bloom, B. S., Masia, B. B. Taxonomy of Educational Objectives: Handbook II: Affective Domain; New York: David McKay Co, 1964.

Lightbown, D. (2015). Designing the user experience of game development tools. Boca Raton, FL: CRC Press.

Murray, T. (2004). Design tradeoffs in usability and power for advanced educational software authoring tools. *Educational Technology*, *44*(5), 10-16.

Naikar, N. (2013). Work domain analysis: Concepts, guidelines, and cases. CRC Press.

Pouw, W. T., Van Gog, T., & Paas, F. (2014). An embedded and embodied cognition review of instructional manipulatives. Educational Psychology Review, 26(1), 51-72.

Ruitenberg, M. F. L., De Kleine, E., Van der Lubbe, R. H. J., Verwey, W. B., & Abrahamse, E. L. (2012). Context-dependent motor skill and the role of practice. Psychological Research, 76(6), 812–820. doi:10.1007/s00426-011-0388-6

Schneider, B., Jermann, P., Zufferey, G., & Dillenbourg, P. (2011). Benefits of a tangible interface for collaborative learning and interaction. Learning Technologies, IEEE Transactions on, 4(3), 222-232.

Schneider, B., Wallace, J., Blikstein, P., & Pea, R. (2013). Preparing for future learning with a tangible user interface: the case of neuroscience. Learning Technologies, IEEE Transactions on, 6(2), 117-129.

Simpson, E. The Classification of Educational Objectives in the Psychomotor Domain: The Psychomotor Domain, Vol. 3; Washington, DC: Gryphon House, 1972.

Soller, A. (2001). Supporting social interaction in an intelligent collaborative learning system. International Journal of Artificial Intelligence in Education, 12(1), 40-62.

Sottilare, R. (2009). Making a case for machine perception of trainee affect to aid learning and performance in embedded virtual simulations. *NATO Research Workshop (HFM-RWS-169) on Human Dimensions in Embedded Virtual Simulations.* Orlando, Florida, October 2009.

Sottilare, R. Considerations in the Development of an Ontology for a Generalized Intelligent Framework for Tutoring. In Proceedings of the International Defense & Homeland Security Simulation Workshop in Proceedings of the I3M Conference. Vienna, Austria, September 2012.

Sottilare, R. Special Report: Adaptive Intelligent Tutoring System (ITS) Research in Support of the Army Learning Model - Research Outline. Army Research Laboratory (ARL-SR-0284), December 2013.

Sottilare, R. A., Brawner, K. W., Goldberg, B. S., & Holden, H. K. (2012). The Generalized Intelligent Framework for Tutoring (GIFT). Orlando, FL: US Army Research Laboratory–Human Research & Engineering Directorate (ARL-HRED).

Sottilare, R.; Gilbert, S. Considerations for Tutoring, Cognitive Modeling, Authoring and Interaction Design in Serious Games. Authoring Simulation and Game-based Intelligent Tutoring workshop at the Artificial Intelligence in Education Conference (AIED) 2011, Auckland, New Zealand, June 2011.

Sottilare, R.; Holden, H.; Goldberg, B.; Brawner, K. The Generalized Intelligent Framework for Tutoring (GIFT); In C. Best, G. Galanis, J. Kerry and R. Sottilare (Eds.) Fundamental Issues in Defence Simulation & Training. Ashgate Publishing, 2013.

Sottilare, R., Sinatra, A., Boyce, M., and Graesser, A. (2015*).* Domain Modeling for Adaptive Training and Education in Support of the US Army Learning Model—Research Outline. *Army Research Laboratory* (ARL-SR-0325), June 2015.

Stanton, N. A. (2006). Hierarchical task analysis: Developments, applications, and extensions. Applied ergonomics, 37(1), 55-79.

Vygotsky, L.S. (1978). Mind in Society: The development of higher psychological processes. Cambridge, MA: Harvard University Press.

AUTHOR BIOGRAPHIES

Dr. Robert A. Sottilare leads adaptive training research within the U.S. Army Research Laboratory where the focus of his research is automated authoring, automated instructional management, and evaluation tools and methods for intelligent tutoring systems. His work is widely published and includes articles in the Cognitive Technology Journal, the Educational Technology Journal, and the Journal for Defense Modeling & Simulation. Dr. Sottilare is a co-creator of the Generalized Intelligent Framework for Tutoring (GIFT), an open-source tutoring architecture, and he is the chief editor for the *Design Recommendations for Intelligent Tutoring Systems* book series. He is a visiting scientist and lecturer at the United States Military Academy and a graduate faculty scholar at the University of Central Florida. Dr. Sottilare received his doctorate in Modeling & Simulation from the University of Central Florida with a focus in intelligent systems. He is the inaugural recipient of the U.S. Army Research Development & Engineering Command's Modeling & Simulation Lifetime Achievement Award (2012).

Dr. Scott Ososky is a Postdoctoral Research Fellow at the Simulation & Training Technology Center (STTC) within the US Army Research Laboratory's Human Research and Engineering Directorate (ARL-HRED). His current research examines mental models of adaptive tutor authoring, including user experience issues related to tools and interfaces within the adaptive tutor authoring workflow. His prior work regarding mental models of human interaction with intelligent robotic teammates has been published in the proceedings of the Human Factors and Ergonomics Society, HCI International, and SPIE Defense & Security annual meetings. Dr. Ososky received his Ph.D. and M.S. in Modeling & Simulation, as well as a B.S. in Management Information Systems, from the University of Central Florida.

Dr. Michael W. Boyce is a Postdoctoral Research Fellow within the US Army Research Laboratory's Human Research and Engineering Directorate (ARL-HRED). As a part of his postdoctoral experience, Dr. Boyce is developing an adaptive tutor using GIFT to support a tactile training environment, the Augmented Reality Sandtable. His research interests involve user interaction design, human systems integration, and human performance assessment. Dr. Boyce received his doctorate in Applied / Experimental Human Factors Psychology from the University of Central Florida.