Using GIFT to Model and Support Students' Metacognition in the UrbanSim Open-Ended Learning Environment

James R. Segedy[1], John S. Kinnebrew[1], Benjamin S. Goldberg[2], Robert A. Sottilare[2], Gautam Biswas[1]
[1]Institute for Software Integrated Systems, Department of Electrical Engineering and Computer Science, Vanderbilt University, 1025 16th Avenue South, Nashville, TN 37212, U.S.A.
[2]U.S. Army Research Laboratory – Human Research and Engineering Directorate, Simulation and Training Technology Center, 12423 Research Parkway, Orlando, FL 32826, U.S.A.

INTRODUCTION

Open-ended computer-based learning environments (OELEs) (Land, Hannafin, & Oliver, 2012; Segedy, Kinnebrew, & Biswas, in press) are learner-centered environments that present students with a challenging problem-solving task, information resources, and tools for completing the task. Students are expected to use the resources and tools to make decisions about how to proceed and in this process learn about the problem domain while developing strategies for task completion and problem-solving. In OELEs, students have to distribute their time and effort between exploring and organizing their knowledge of the problem domain, creating and testing hypotheses, and using their learned knowledge to make progress toward goals (which are often problems that have multiple solution paths). Since there are no prescribed solution steps, students may have to discover the solution process using exploratory methods. Moreover, there may not be an obvious, single "best" solution to a problem. Therefore, the exploration process may require students to consider trade-offs and employ their critical thinking and evaluation skills that progressively lead them to achieving a good solution.

Succeeding in OELEs can be difficult because of the cognitive and metacognitive demands that such environments place on learners. To solve problems as they learn about a new domain, students have to simultaneously wrestle with their emerging understanding of a complex topic, develop and utilize skills to enable and support their learning, and employ self-regulated learning (SRL) (Zimmerman & Schunk, 2011) processes for managing the open-ended nature of the task. As such, OELEs can prepare students for future learning (Bransford & Schwartz, 1999) by developing their ability to independently investigate and develop solutions for complex open-ended problems.

In this paper, we discuss our recent work in integrating the UrbanSim counter-insurgency (COIN) command simulation (McAlinden, Durlach, Lane, Gordon, & Hart, 2008) and the Generalized Intelligent Framework for Tutoring (GIFT). The goal of this work is to develop general representations and authoring tools for monitoring and supporting students' *metacognitive thinking*, a vital component of SRL, while using OELEs such as UrbanSim. Metacognition (Brown, 1975; Flavell, 1976) describes the ability to reason about and explicitly manage one's own cognitive processes. In particular, our work is centered on students' understanding and use of *strategies*, which have been defined as consciously-controllable processes for interpreting, analyzing, and completing tasks (Pressley, Goodchild, Fleet, Zajchowski, & Evans, 1989).

Towards this end, we have recently conducted a study with students from a University Reserve Officers' Training Corp (ROTC) program who used the UrbanSim OELE through GIFT as part of their regular classroom activities. Before and after students used the system, we asked them to explain their understanding of COIN and the steps involved in conducting a COIN operation. We present a qualitative analysis of our initial results from this study that shows students learned about COIN doctrine and also developed or refined their strategies for information acquisition and planning to support COIN operations in a realistic scenario (in the UrbanSim simulation environment). These early results are encouraging, and we expect to gain valuable insight from the collected data, such as how students' strategies evolved as they worked with UrbanSim over the course of the study. Our overall goal is to develop a metacognitive tutor for UrbanSim using the GIFT authoring tools that will support and help students learn metacognitive problem solving strategies when working on complex COIN problems in the UrbanSim environment.

BACKGROUND

Metacognition (Flavell, 1976) describes the ability to reason about and explicitly manage one's own cognitive processes. It is often broken down into two sub-components: knowledge and regulation (Schraw, Crippen, & Hartley, 2006; Young & Fry, 2008). Metacognitive knowledge refers to an individual's understanding of their own cognition and strategies for managing that cognition. Metacognitive regulation refers to how metacognitive knowledge is used for creating plans, monitoring and managing the effectiveness of those plans, and then reflecting on the outcome of plan execution in order to develop and refine metacognitive knowledge (Veenman, 2011).

When applied to learning, metacognition can be considered a subset of self-regulated learning (SRL). SRL is a theory of active learning that describes how learners are able to set goals, create plans for achieving those goals, continually monitor their progress, and revise their plans to make better progress in achieving these goals (Zimmerman & Schunk, 2011). In terms of SRL, metacognition deals directly with cognition without explicitly considering its interactions with emotional or motivational constructs (Whitebread & Cárdenas, 2012). Despite this separation, models of self-regulation are valuable in depicting key metacognitive processes. For example, Roscoe, Segedy, Sulcer, Jeong, & Biswas (2013) describe SRL as containing "multiple and recursive stages incorporating cognitive and metacognitive strategies" (p. 286). This description of SRL involves phases of orientation and planning, enactment and learning, and reflection and self-assessment.

Our focus on metacognition is centered on students' understanding and use of *strategies*, which have been defined as consciously-controllable processes for completing tasks (Pressley et al., 1989). Strategies comprise a large portion of metacognitive knowledge; they consist of declarative, procedural, and conditional knowledge that describe the strategy, its purpose, and how and when to employ it (Schraw et al., 2006). The research community has identified several types of strategies based on the tasks for which they are designed. Strategies may be cognitive (*e.g.*, a strategy for applying a particular procedure, or completing an addition problem), metacognitive (*e.g.*, strategies for choosing and monitoring one's own cognitive operations), involve management (*e.g.*, for managing one's environment to promote focused attention), be directed toward learning (*e.g.*, a strategy for memorizing new information), or involve a combination of these (Pressley et al., 1989). For example, a metacognitive learning strategy might involve *activating prior knowledge* before reading about a topic by consciously bringing to mind information one already knows about the topic (Bouchet, Harley, Trevors, & Azevedo, 2013). When faced with a complex task, students must either identify/adapt a known strategy for completing it or invent one using their metacognitive knowledge.

An important characteristic of a strategy is its *level of generality*. That is, some strategies apply to very specific situations (*e.g.*, an approach to adding two-digit numbers) while other strategies apply to a broader set of situations (*e.g.*, summarizing recently learned information to improve retention). An understanding of more general strategies, as well as their specific implementations for concrete tasks, is important for developing one's ability to adapt existing strategies to new situations or invent new strategies. Thus, our goal in GIFT is to explicitly teach students general strategies and help students understand how to apply them to complex tasks. In the longer run, as students encounter different situations in which a strategy applies, we hope to make students aware of how strategies, such as those for maintaining situational awareness, monitoring the execution of one's plan, and evaluating the benefits and drawbacks of a previously-executed task, may generalize across tasks and domains (Bransford & Schwartz, 1999). A pre-requisite to achieving this goal in the GIFT framework is the ability to conceptualize and build domain-independent structures for representing metacognitive strategies and processes.

THE URBANSIM OPEN-ENDED LEARNING ENVIRONMENT

UrbanSim (McAlinden et al., 2008), shown in Figure 1, is a turn-based simulation environment in which users assume command of a COIN operation in a fictional Middle-Eastern country. Users have access to a wealth of information about the area of operation, including: intelligence reports on key individuals, groups, and structures; information about the stability of each district and region; economic, military, and political ties between local groups in the region; the commanding team's current level of population support; and the team's progress in achieving six primary lines of effort. Users have a limited amount of resources at their command to perform the COIN operations, and the actions that users take are scenario-specific, but they generally have to be directed toward increasing the area's stability by making progress along the different lines of effort: (1) improving civil security; (2) improving governance; (3) improving economic stability; (4) strengthening the host nation's security forces; (5) developing and protecting essential services and infrastructure; and (6) gaining the trust and cooperation of the population.

Figure 1. UrbanSim

Students conduct their operations by assigning orders to available units under their command (*e.g., E CO b* and *G CO a* in Figure 1). To commit their orders, they press the *COMMIT FRAGOS* (FRAGmentary OrderS) button to complete one turn in the simulation environment. The simulation then executes the user's orders; simultaneously, it has access to a sociocultural model and complementary narrative engine that jointly determine the actions of non-player characters in the game. These non-player actions also affect the simulation results. For example, a friendly police officer may accidentally be killed during a patrol through a dangerous area. These *significant activities* and *situational reports* are communicated to the user, and the combination of all activities may result in net changes to the user's population support and line of effort scores (see bottom right of Figure 1).

UrbanSim provides documentation and tutorials that help students gain an appreciation for the challenges inherent in managing COIN operations. For example, they should learn the importance of maintaining situational awareness, managing trade-offs, and anticipating 2^{nd}- and 3^{rd}-order effects of their actions, especially as the game evolves (McAlinden et al, 2008). They should also understand that their actions themselves produce intelligence and, therefore, they need to continually "*learn and adapt*" in such complex domains with overwhelming, yet incomplete, information. In other words, students should realize that their decisions result in new information that may be critical for decision making and planning during upcoming turns. Students can learn about the effects of their actions by viewing causal graphs provided by their intelligence and security officer (S2). Users who adopt strategies to better understand the area of operation and its culture by viewing and interpreting the effects of their actions using these causal graphs should progressively make better decisions in the simulation environment as the COIN scenario evolves.

UrbanSim Learner Model

To represent metacognition in GIFT, we are currently designing extensions to its learner modeling capabilities. In GIFT, a learner model consists of a set of named *concepts* that are assessed continually while students are interacting with designated course materials. At any time, each concept may be assessed as below, at, or above expectation, and higher-level concepts may be related hierarchically to lower-level concepts. Thus, a *basic mathematics* concept may be based on assessments of its component concepts: *addition*, *subtraction*, *multiplication*, and *division*. The data representation is similar to the sampling of a stream: GIFT monitors each student's task performance over time, updating the concept assessments based on his or her most recent performance. Thus, a student may perform above expectation on one subtraction problem and below expectation on the next. A history of these assessments is maintained for feedback purposes, both during and after learning.

Building from this, we will employ a three-level framework for analyzing and representing students' skill and strategy proficiency, shown in Figure 2. Analyses will involve making a set of inferences based on students' observed behaviors while using the learning environment. In this framework, direct observations of students' behaviors will serve as assessments of their ability to correctly execute strategies. To accomplish this, we are designing tools that allow course designers to specify how actions can be combined to enact a strategy. The resulting strategy model can be used online to interpret students' action sequences in terms of these strategies. The strategy that best matches students' behaviors will be assumed to be the strategy they are applying, and further assessments will examine whether or not they execute the strategy correctly. For example, a student may be using a monitoring strategy in which they check their recently-completed work to make sure it is correct. However, they may erroneously conclude that their work was completed correctly, indicating an ineffective execution of the strategy.

These assessments and interactions, along with continued monitoring of student behavior, will serve as the basis for assessing students' understanding of domain-specific strategies. When GIFT observes a correctly-executed strategy, it will increase its confidence in the student's understanding of the associated procedural knowledge. Similarly, when GIFT observes a strategy executed at an appropriate time, it will increase its confidence in the student's understanding of the associated conditional knowledge. To test students' declarative knowledge, GIFT will interact with them directly through conversational assessment techniques to better infer their understanding.

The final (top) level of our framework involves linking students' understanding of task-specific strategies to task-general representations of those strategies. An important aspect of metacognition is that the declarative knowledge for a number of strategies can be expressed in a domain-general form. In other words, many strategies can be applied to multiple tasks, situations, and contexts. Our approach leverages this property by developing new GIFT capabilities for tracking and supporting task-general strategies in multiple contexts. When a student correctly employs a task-specific strategy, GIFT will link this use of the strategy to its task-general representation and the context in which the strategy was applied. This information will be stored in GIFT's long-term learner model and can be referenced during future learning sessions. The goal is to integrate information about strategy use across multiple contexts, allowing GIFT to provide instruction and guidance that draws connections between a learner's current tasks and their previous experiences. For example, GIFT could guide the student through an analogy: "*This task is just like when you had to do [X] in [ENV] back in [MONTH]. The main difference is [Y].*" Next steps will involve defining pedagogical representations that are informed by this learner modeling approach, and how guidance functions will be managed across the varying levels of abstraction.

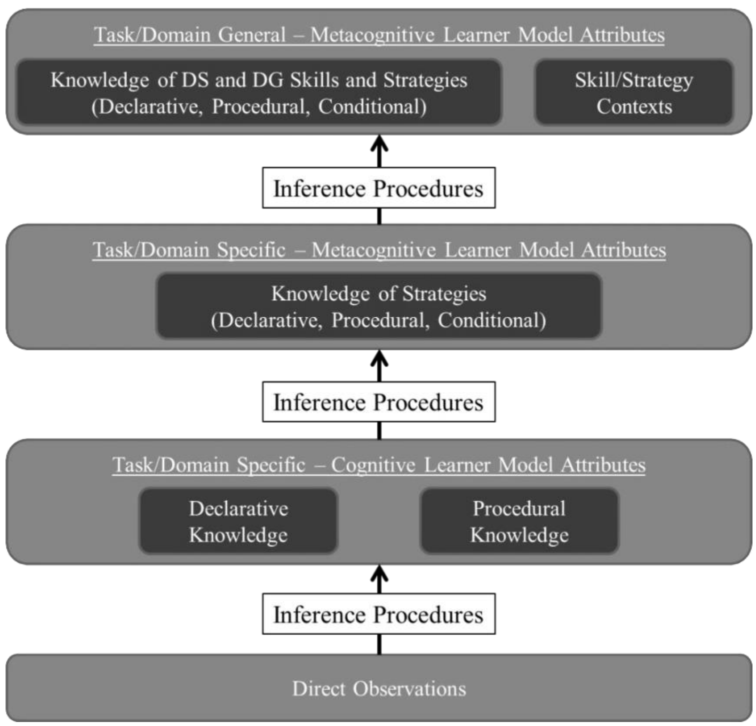

Figure 2. Skill and Strategy Detection Framework

Connecting UrbanSim to GIFT

In order to connect UrbanSim to GIFT, we created a Java application that monitors the UrbanSim log files and publishes the information to any interested parties. The various components and their interactions necessary for connecting UrbanSim and GIFT are shown in Figure 3. UrbanSim produces log files that include information on the actions taken in the simulation and the effects of those actions. Our log parser reads these files as they are created and communicates the *actions* taken by learners as well as the *contexts* in which those actions occur. In this instance, a context can be considered to be equivalent to an interface configuration. For example, the configuration shown in Figure 1 displays a map of the area of operation. By tracking the actions and contexts logged by UrbanSim, we are able to create a detailed understanding of students' behaviors in the program.

In the tutor we used during our preliminary study, we configured GIFT to detect when students commit their orders and present them with a survey through GIFT's tutor user interface, as shown in Figure 4. The survey asked students the following questions:

- What were your goals when you committed these FRAGOs?
- How did you expect these FRAGOs to help you achieve your goals?
- What trade-offs or negative effects did you expect as a result of these FRAGOs?
- How was your approach this turn different from your last turn (if applicable)?
- Did your FRAGOs have the effect you had intended? Why or why not?
- Were the outcomes of your FRAGOs the same, worse, or better than what you expected? Why do you think that?
- If offered another opportunity, what would you do differently on the turn you just completed?

We expect that the data collected through this survey will provide valuable insights into how students analyze situations in UrbanSim and learn from them as the simulation progresses.

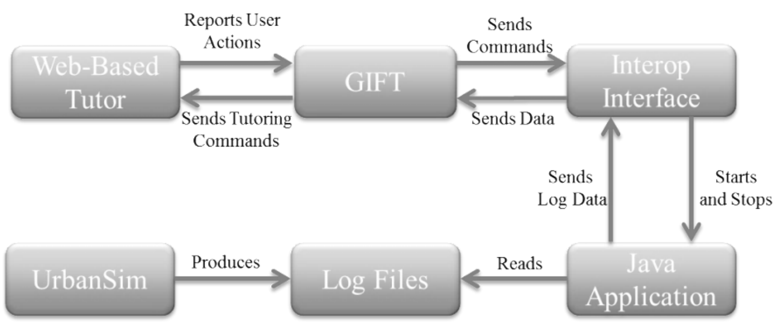

Figure 3. Communication between GIFT and UrbanSim

PRELIMINARY STUDY OF ROTC STUDENTS USING URBANSIM

The goal of our preliminary study of ROTC students was to collect data on students' use of the system. In particular, we were interested in data about students' goals, approaches, strategies, expectations, surprises, interpretations, and understanding of COIN concepts. This will help us identify the primary metacognitive strategies that we will incorporate into a metacognitive GIFT tutor for UrbanSim.

Fourteen senior-year ROTC students from a Southeastern United States university participated in the study. These students worked in pairs during two separate 2-hour sessions (approximately one month apart). Due to absences, these 14 students comprised 8 groups during the two sessions, with 4 groups remaining the same for both sessions. Students used UrbanSim to practice COIN in two scenarios: Al-Hamra and Al-Hamra 2. In both scenarios, they had access to intelligence on the area of operation, including its key structures, individuals, and groups. Their mission in the Al-Hamra scenario was to "restore Al-Hamra's civil infrastructure and ensure the happiness and productiveness of the population." In Al-Hamra 2, they were charged with establishing "successful government and security that meets the needs of its citizens while stopping the flow of extra-national insurgents."

The study proceeded as follows: (1) students completed a pre-activity survey asking them about their experience with and understanding of COIN; (2) students used UrbanSim with the Al-Hamra 2 scenario for approximately 90 minutes; (3) students used UrbanSim with the Al-Hamra scenario for approximately

90 minutes; (4) the course professor led a debriefing discussion with the students; and (5) students completed a post-activity survey. The surveys included two questions analyzed in this paper: (1) Please briefly explain, in your own words, how the Clear-Hold-Build doctrine applies to counter-insurgency operations; (2) Imagine that you have been assigned command of a counter-insurgency operation. Explain the steps you would go through before formulating your own mission plan and lines of effort.

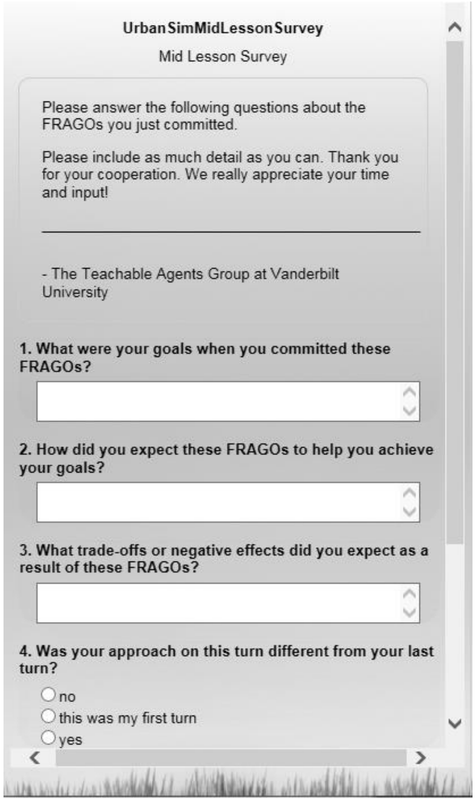

Figure 4. UrbanSim survey presented through GIFT

During the study, we collected several streams of data, including: (1) log files from UrbanSim and GIFT; (2) pre- and post- activity surveys and post-turn surveys; and (3) audio-video data from the computer web-cams synced to a screen capture video. In the next section, we present a preliminary qualitative analysis of the pre- and post- activity survey responses.

PRELIMINARY RESULTS

In analyzing students' survey data, our primary finding was that after students used GIFT and UrbanSim, their survey answers , in general, became more specific. Thus, there is evidence that the experience with GIFT and UrbanSim helped students gain a more concrete understanding of the essence of COIN operations and how they evolve over time. Further, the additional details in the COIN operations planning question on the post-survey suggest that students developed or refined strategies for COIN information acquisition and planning. To illustrate these preliminary findings, we present selected answers from the two survey questions listed in the previous section.

Explaining Clear-Hold-Build

Clear-Hold-Build (CHB) is a counter-insurgency strategy with three distinct phases. First, military forces *clear* an area of insurgents. Second, they focus on *holding* the cleared area and preventing further insurgent infiltration. Third, they focus on *building* up the area's government, police forces, and infrastructure such that the local population is able to safeguard the area independently.

Most students demonstrated a basic understanding of these principles during both the pre-survey and post-survey. However, four students indicated that they did not know what clear-hold-build was during the pre-survey. Typical answers to this survey question mentioned the three phases and included a high-level description of each phase. Pre-survey answers included the following:

- **User A09**: *Clear: taking over control of a certain area – eliminating enemy presence. Hold: maintain a presence in the community. Build: restore important economic infrastructure & build up the civilians' trust in our mission.*

- **User A12**: *Clear-Hold-Build is a progressive method for establishing security and stability over a given area by first conducting patrols, cordons and other military operations to secure the area, maintain a constant presence and gradually construct vital institutions – governance, infrastructure, police, public works, etc. – to gain support of the population.*

All students were able to explain CHB during the post-survey with about the same level of detail as on the pre-survey:

- **User A09**: *Clear - eliminate the enemy; Hold - maintain presence in area; Build - reconstructive efforts.*

- **User A12**: *An area must initially be cleared of insurgents in a dynamic military operation, then security must be established and control imposed within an area. Finally infrastructure and essential services need to be built within the area to secure the support of the population.*

Overall, students who were unfamiliar with CHB on the pre-survey understood it after using GIFT and UrbanSim.

Explaining Steps for Formulating a Counter-Insurgency Plan

During the pre-survey, students' answers to this question were fairly general; they could apply to almost any mission and often lacked focus and prioritization relevant to the task. Typical answers included:

- **User A11**: *Understand civilian support of insurgents and coalition forces. Understand the general conditions of the area & its importance.*

- **User A14**: *I would discuss w/my command team our intent and the best way to complete our mission.*

One student did provide a more involved pre-survey answer: *(1) Where am I? I need to know the history, geography, and cultural norms of the locals. Who are the local leaders? (2) What do the insurgents want? What do they use as recruitment tools? (3) What forces, both US & local, are available to me? Do I have adequate funding?*

Compared to the pre-survey, answers on the post-survey were more detailed. These answers included:

- **User A11**: *I would investigate how strong the insurgents are and where they seem to be centralized and then meet w/local leaders to see what lines of effort are most important to them.*

- **User A14**: *I would hold meetings w/key leaders in area, as well as soldiers/staff that are familiar w/area and then decide on areas and priorities to focus on and then start my plan.*

These answers are more specific than those from the pre-survey, indicating that students may have developed more concrete, focused strategies for planning and information acquisition in COIN operations.

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

In this paper, we have described our approach for developing and incorporating a metacognitive tutoring framework into the GIFT platform. Our approach leverages research on metacognition, strategies, and strategy instruction with open-ended learning environments to track students' understanding and use of strategies for complex problem-solving scenarios. Moving forward, we will continue developing this framework, incorporate it into GIFT, and instantiate it with the UrbanSim counter-insurgency simulation.

The results of our preliminary data analysis indicate that students did learn as a result of using GIFT and UrbanSim, including developing and refining strategies for COIN operations. This early positive indication is encouraging, and we expect to gain valuable insights into students' strategy uses from the rich data we have collected in the study. We plan on identifying strategies used by students and working with ROTC instructors to identify which of these strategies are more and less effective in general, and why. We are currently investigating the following: (1) How well do students utilize the information available to them in UrbanSim? (2) What strategies do students understand and execute (in)effectively? (3) What do student pairs discuss as they use the simulation, and how does this provide indications of their understanding of strategies? (4) How well do their LOE priorities align with the goals of the mission, and which LOEs do students focus on and ignore?

In parallel, we are working with GIFT developers to begin implementing our metacognitive framework for strategy identification and ultimately use students' current behavior and prior experiences to direct scaffolding. Our analysis of protocols of student discussions as they worked on UrbanSim will provide us with initial data on use of strategies and the context in which they are applied. More advanced analyses will involve the application of analytic measures and sequence mining techniques to develop and refine strategy identification methods over time, which in turn will better inform state representations that trigger scaffolding.These combined analyses will allow for powerful tutoring interactions between students and GIFT.

REFERENCES

Bouchet, F., Harley, J., Trevors, G., & Azevedo, R. (2013). Clustering and profiling students according to their interactions with an intelligent tutoring system fostering self-regulated learning. *Journal of Educational Data Mining, 5*(1), 104-146.

Bransford, J., & Schwartz, D. (1999). Rethinking transfer: A simple proposal with multiple implications. *Review of Research in Education, 24*(1), 61-101.

Brown, A. (1975). The development of memory: Knowing about knowing, and knowing how to know. In H. Reese (Ed.), *Advances in Child Development and Behavior* (pp. 103-152), New York, NY: Academic Press.

Flavell, J. (1976). Metacognitive aspects of problem solving. In L. Resnick (Ed.), *The Nature of Intelligence* (pp. 231-236). Hillsdale, NJ: Erlbaum.

Land, S., Hannafin, M., & Oliver, K. (2012). Student-centered learning environments: Foundations, assumptions and design. In D. Jonassen & S. Land (Eds.), *Theoretical Foundations of Learning Environments* (pp. 3-25). New York, NY: Routledge.

McAlinden, R., Durlach, P., Lane, H., Gordon, A., & Hart, J. (2008). UrbanSim: A game-based instructional package for conducting counterinsurgency operations. In: *Proceedings of the 26th Army Science Conference*, Orlando, FL.

Pressley, M., Goodchild, F., Fleet, J., Zajchowski, R., & Evansi, E. (1989). The challenges of classroom strategy instruction. *The Elementary School Journal, 89*, 301-342.

Schraw, G., Crippen, K., & Hartley, K. (2006). Promoting self-regulation in science education: Metacognition as part of a broader perspective on learning. *Research in Science Education, 36*(1), 111-139.

Segedy, J.R., Kinnebrew, J.S., & Biswas, G. (in press). Using coherence analysis to characterize self-regulated learning behaviours in open-ended learning environments. *Journal of Learning Analytics*.

Veenman, M. (2011). Learning to self-monitor and self-regulate. In R. Mayer & P. Alexander (Eds.), *Handbook of Research on Learning and Instruction* (pp. 197-218). New York, NY: Routledge.

Whitebread, D., & Cárdenas, V. (2012). Self-regulated learning and conceptual development in young children: The development of biological understanding. In A. Zohar & Y.J. Dori (Eds.), Contemporary Trends and Issues in Science Education: Vol. 40. *Metacognition in Science Education: Trends in Current Research* (pp. 101-132). Netherlands: Springer Science+Business Media.

Young, A. & Fry, J. (2008). Metacognitive awareness and academic achievement in college students. *Journal of the Scholarship of Teaching and Learning, 8*(2), 1-10.

Zimmerman, B., & Schunk, D. (Eds.). (2011). *Handbook of Self-Regulation of Learning and Performance*. New York, NY: Routledge.

ABOUT THE AUTHORS

Dr. James R. Segedy *is a Postdoctoral Research Scholar in the Teachable Agents Group at Vanderbilt University. His research focuses on developing measures of open-ended and independent problem solving behaviors for use by classroom teachers. His work has also included developing adaptive scaffolds such as contextualized conversational feedback and guided practice in open-ended learning environments.*

Dr. John S. Kinnebrew *is a Research Scientist at the Institute for Software Integrated Systems at Vanderbilt University. He is currently involved in a variety of computer-based learning environment projects, where his research focuses on data mining and machine learning for modeling human learning behaviors, including metacognition and self-regulated learning strategies.*

Dr. Benjamin Goldberg *is an adaptive training scientist at the Army Research Laboratory's SFC Paul Ray Smith Simulation & Training Technology Center. He leads research focused on instructional management within ARL's Learning in Intelligent Tutoring Environments (LITE) Lab and is a co-creator of the Generalized Intelligent Framework for Tutoring (GIFT).*

Dr. Robert Sottilare *is the Chief Scientist at the Army Research Laboratory's SFC Paul Ray Smith Simulation & Training Technology Center. He leads adaptive training research within ARL's Learning in Intelligent Tutoring Environments (LITE) Lab and is a co-creator of the Generalized Intelligent Framework for Tutoring (GIFT).*

Dr. Gautam Biswas *is a Professor of Computer Science, Computer Engineering, and Engineering Management in the EECS Department and a Senior Research Scientist at the Institute for Software Integrated Systems (ISIS) at Vanderbilt University. conducts research in Intelligent Systems with primary interests in simulation, and analysis of complex embedded systems, their applications to diagnosis, prognosis, and fault-adaptive control, and the design and development of Computer-Based Learning Environments. His research has been supported by funding from ARL, NASA, NSF, DARPA, and the US Department of Education.*