Enhancing Self-Regulated Learning through Metacognitively-Aware Intelligent Tutoring Systems

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Abstract: This symposium identifies current trends and future directions in research on metacognition and Self-Regulated Learning (SRL) in educational technologies, and specifically, Intelligent Tutoring Systems (ITS). Each paper will elaborate on detection and assessment of metacognition/SRL, forms of support and scaffolding, and self- and co-regulation processes and authoring of environments that support ITS. The symposium will conclude with discussions that describe the manner in which metacognitive development can be promoted through strategies that support individual differences in multiple contexts. The alternative perspectives presented in this session will help advance our understanding of support for metacognition and SRL in ITS, as well as identify gaps that will influence future research pursuits.

Overall Focus of the Symposium

Intelligent Tutoring Systems (ITS) are designed to manage and regulate learning experiences within a specified domain. While shown to be effective in helping individuals gain new knowledge and learn problem solving procedures, a typical ITS confines its pedagogical approach to the domain material alone, with little emphasis on promoting metacognitive learning strategies that are general across domains. Recent research strives to enhance such systems through the incorporation of tools and methods that promote Self-Regulated Learning (SRL) by incorporating strategies linked to metacognitive awareness and regulation. Metacognition is often described as being made up of two constituent parts: (1) *Metacognitive knowledge*, which is declarative and deals with the interplay between knowledge of one's abilities to perform tasks, the nature of the task, and the strategies one can employ to successfully perform the task; and (2) *Metacognitive regulation*, which includes activities related to goal selection, planning, monitoring, control, and reflection (Flavell et al., 1985; Schraw et al., 2006; Veenman, 2012). Because metacognition involves the explicit management of one's own cognitive resources, there exist strong interrelationships between learners' metacognitive abilities and their understanding of, familiarity with, and effectiveness in executing the cognitive tasks required for success (Bransford, et al., 2000; Winne, 1996). Thus, tutors in open-ended environments must be able to measure and interpret student behaviors at both the cognitive and metacognitive level in order to provide support for both types of mental processes (Biswas, et al., 2010; Land, 2000; Kramarski, 2004; Roll, Aleven, McLaren, & Koedinger, 2007). The purpose of this symposium is to present current research and perspectives that address this problem space from relevant experts in the field.

This session includes four papers that adopt the common theme of using technology-based instructional systems to help students become more independent learners. Presentations will cover research derived from models and constructs linked to SRL, modeling and monitoring techniques to gauge students' cognitive and metacognitive abilities, defined strategies and tactics for guiding and improving metacognitive processes, and implications for developing authoring tools to facilitate monitoring, modeling, and scaffolding metacognitive processes in an ITS. Collectively, the presentations will be oriented toward discussing pragmatic issues associated with supporting metacognition and SRL in ITSs, and how the application of metacognitive strategies can enhance learning outcomes as they relate to improved learning performance and transfer. As metacognition deals with one's awareness of the knowledge and regulation of cognition, it is important to understand the distinctions between these two parts and how they compliment learning within SRL environments that are open-ended in nature. In turn, ITS developers need to understand how individuals apply metacognitive strategies to fully embed modeling techniques and pedagogical strategies that fit within the theoretical constructs of how students regulate resources and emotions when learning. This includes looking at various modeling approaches that take into account theoretical foundations associated with a domain, along with methods to monitor actions in an environment to identify patterns of successful behavior that may be linked to metacognitive strategies. In addition, the use of instructional strategies to improve students' metacognition must be explored, looking both at triggers (i.e., static vs. adaptive) and distinguishing characteristics of strategies as they relate to the varying processes linked to learning (i.e., cognition, behavior, motivation, and affect). Furthermore the application of ITS technologies outside of academic settings (i.e., K-12) is becoming more prevalent, with a push for systems to support simulations in real-world contexts. Student profiles and learner models must now accommodate the life-long adult learner. Implications for tailoring systems to support individuals in varying phases of their life and career must be identified, as these characteristics will dictate how systems will adapt to aid in the development of independent learning skills. In addition to establishing a foundation for how to assess and instruct metacognitive behaviors, we describe tools to author these mechanisms into an Intelligent Tutor.

A Combined Theory- and Data-Driven Approach for Interpreting Learners' Metacognitive Behaviors in Open-Ended Learning Environments

Gautam Biswas, James R. Segedy, John S. Kinnebrew, ISIS/ Department of EECS, Vanderbilt University

Adapting to learners' needs and providing useful individualized feedback to help them succeed has been a hallmark of most intelligent tutors (Anderson, et al., 1995; Gertner & Van Lehn, 2000). More recently, to promote deep learning, critical thinking, and problem-solving skills in STEM disciplines, researchers have begun developing tutoring systems that present learners with complex problems and a set of tools for learning and problem-solving (Hannafin, 1994; Land, 2000). To be successful in such open-ended learning environments (OELEs), learners must be metacognitively aware, apply metacognitive strategies that promote effective learning, and manage, coordinate, and reflect on their use of a number of cognitive processes to succeed in their learning and problem solving tasks (Bransford et al., 2000; Zimmerman, 2001). A typical learning task may combine a number of activities, such as searching for information, interpreting information in the context of the learning and problem solving tasks, and applying it to the construction and testing of potential problem solutions. This can present significant challenges to novice learners; they may have neither the proficiency for using the system's tools nor the experience and understanding necessary for explicitly regulating their learning and problem solving (Chi et al., 1988; VanLehn, 1996). Furthermore, their abilities to reflect on past activities and relate them to task outcomes may not be well developed (Schunk & Zimmerman, 1997). Not surprisingly, research has shown that novices often struggle to succeed in such complex environments.

Measuring Metacognition in Open Ended Learning Environments (OELEs)

Adaptive tutoring systems regularly capture and analyze student activities in order to make decisions about how and when to scaffold learners. However, the complexity of OELEs poses considerable challenges to accurately interpreting and understanding student behaviors. Traditionally, learning behavior is assessed with top-down metrics based on theory and hypotheses about student learning activities in the context of their learning tasks (Hmelo-Silver, 2004; Segedy, Loretz, & Biswas, 2013). In recent years, however, bottom-up data mining techniques that analyze students' logged activity data have been utilized to discover important aspects of how students learn (Kinnebrew, Loretz, & Biswas, 2013). We present a framework for analyzing learning activity data in OELEs that combines top-down metrics and bottom-up pattern discovery. This integrated framework can be employed to build detailed models of students' learning behaviors and strategies, and subsequently to identify opportunities for providing adaptive scaffolds to students as they use the system.

For top-down, theory-driven analysis of learning behaviors, our framework focuses on (i) the learner's acquisition and application of knowledge and information encountered while they perform their task-related activities in the OELE and (ii) the impact of these activities with respect to the learning task (e.g., whether an action directly resulted in progress toward completion of the task). For bottom-up, data-driven discovery of learning behaviors, our framework employs data mining techniques for identifying frequent patterns of action in logs of their activity in the environment. Our approach enhances the analysis and assessment of student learning behavior by combining these complementary top-down and bottom-up techniques. This allows us to identify specific learning behaviors for a group of students, behavior differences between groups that are relevant to understanding their approach to learning in the environment, and the connections between specific patterns of activity and the relevant skills or strategies for learning and problem solving. More specifically, the theory-driven metrics are used for evaluating and differentiating instances of the discovered patterns in order to better understand whether or not the discovered patterns were used as part of coherent strategies and, if so, which ones. The theoretical measures also provide valuable information about individual differences among students that may employ the same pattern of actions but in different manners or for different purposes. Therefore, this analysis framework provides concrete results in the form of action patterns with associated measures that are linked to relevant learning strategies and behaviors.

Case Study: Application to the Betty's Brain OELE

Betty's Brain is an open-ended learning environment (Biswas, et al., 2005) that provides students with a learning context and a set of tools for pursuing authentic and complex model building tasks. Students working in the Betty's Brain system are expected to apply a number of cognitive skills that relate to the four primary activities that the students can perform in the environment: (1) read and understand the science content, (2) translate the relevant content into specific causal relations to build the causal map to teach Betty, a computer agent, (3) check the correctness of the causal map by asking Betty questions and getting her to take quizzes, and (4) use the quiz and question results to identify the correct, incorrect and incomplete parts of the map. Together (1) and (2) are referred to as *Knowledge Construction* skills, and (3) and (4) are referred to as *Solution Evaluation* skills. Building up from the cognitive skills, we hypothesize four categories of metacognitive strategies that students need to develop and deploy in the Betty's Brain environment: (1) Goal Setting & Planning, (2) Knowledge Construction, (3) Solution Evaluation, and (4) Help Seeking (Kinnebrew, Segedy, & Biswas, 2014).

An important aspect of our hierarchical task model is its non-linearity; students are expected to continually navigate among the cognitive and metacognitive processes as they go about their task of teaching Betty a correct and complete map of the domain. Thus, this model also serves as a framework for interpreting students' learning activities and activity sequences that we characterize as learning behaviors. This matches other approaches (e.g. (Hadwin et al., 2007)) that describe students' evolving metacognition in terms of a sequence of events using trace methodologies. The structure of the model also implies that it is unlikely students can be effective in metacognitive strategies unless they are proficient in the related cognitive strategies.

Our analytic framework for analyzing OELE learning activity data comprises extracting sequences of canonical actions from log files of student activities, sequential pattern mining to identify common action patterns, mapping identified patterns back into action sequences to analyze them with the theory-driven measures in the context of the students' other activities, and linking the identified behaviors (described by both a sequential pattern of actions and the relevant measure values that distinguish it from other instances of the same action pattern) to skills and strategies in the cognitive/metacognitive task model. To assess a student's metacognitive regulation, our approach evaluates student behaviors using a measure of coherence called *action support*. Support for a particular student action represents the extent to which it is informed by information gained from previous actions. For example, information seeking actions (e.g., reading about a causal relationship) can provide support for future solution construction actions (e.g., adding the corresponding causal link to the map). Students with higher proportions of supported actions are considered to have a higher mastery of strategies for coordinating their use of tools within the environment.

We present results from analyzing data from recent studies with Betty's Brain that we have run in middle school science classrooms. The results of this analysis provide a foundation for developing performance- and behavior-based learner models in conjunction with adaptive scaffolding mechanisms to promote effective, personalized learning experiences.

Assessment and Instruction of Self- and Co-Regulation of Medical Diagnostic Processes in Technology-Rich Learning Environments

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Broadly speaking, learning is often described in terms of the relationship between what goes on in the mind and how the environment influences what is learned. By environment we refer to: the learning materials presented in or outside of class; the real or augmented context; the presence and influence of others (human or computer-supported) be they peers, tutors or teachers, and; the structure of the environment (ill-structured or structured). We are seeing an evolution in the constructs of SRL that better articulate the components of the environment that need to be considered in defining and supporting SRL. In this paper, we describe BioWorld (Lajoie et al., 2013), a computer based learning environment (CBLE) in terms of how it supports learners' SRL of diagnostic reasoning processes while solving virtual patient cases.

Fostering Regulatory Processes in Diagnostic Reasoning with BioWorld

The social cognitive perspective of SRL states that self-regulation involves cognitive, affective, motivational., and behavioral activities that are planned and adapted in order to attain a goal., such as solving a problem (Zimmerman, 2000). Problem-solving processes occur in three phases: forethought, performance, and self-reflection. Self-reflection processes occur after performance efforts, and in turn, influence forethought in relation to subsequent steps taken to solve the problem. SRL processes are recursive in that feedback from prior performance informs subsequent adjustments efforts (Zimmerman & Campillo, 2003). We apply SRL theories to phases of problem-solving processes relevant to domain-specific knowledge involved in diagnostic reasoning.

BioWorld is designed to foster SRL by supporting cognitive and metacognitive activities that are critical in diagnosing virtual patient cases. Forethought processes involve learners' efforts to orient themselves to a patient problem, and plan the necessary next steps. Self-regulated learners activate their prior knowledge of disorders in response to relevant information pertaining to the case in an effort to list hypothetical diagnoses. A typical learner might then formulate a plan to order a lab test that will confirm the most likely diagnosis, look for particular information from the library, or seek external help by asking for a consult. During the performance phase, learners execute the steps, and then monitor the outcomes. After receiving the outcomes of a lab test for instance, learners determine whether the results are pertinent or non-pertinent to the diagnosis. In doing so, learners might determine that their overall understanding of the case improved, or if their test results are unexpected, or contradictory, confusion may occur which may lead to a re-evaluation of the plausibility of the tentative diagnoses. Self-reflection processes consist of learners' evaluation of and elaboration on their overall progress in problem solving. Self-regulated learners check the relevant evidence and symptoms, while at the same time verifying each hypothetical diagnosis. A typical learner connects evidence and relevant information by drawing conclusions and updating their confidence in each diagnosis.

Assessing Novices along the Trajectory towards Expertise

A learner model is a computational representation of learner characteristics that includes relevant states pertaining to knowledge and skill acquisition as inferred through their interaction with the learning environment (Shute & Zapata-Rivera, 2012). The representation of relevant learner characteristics is continually updated throughout the learning session as they practice their skills. Learner interactions are recorded and analyzed by the CBLE with the aim of guiding instruction. Table 1 shows an overview of learner modelling techniques used for the purposes of assessing SRL in BioWorld. The current version of BioWorld implements a novice-expert overlay model to deliver feedback. This method relies on the comparison of novice actions to the expert solution trace. These actions are recorded through the evidence palette, which is designed to assist novices in orientating themselves to the problem space (i.e., patient symptoms highlighted in case description, relevant library information accessed, lab tests ordered etc.). The feedback palette shows similarities and differences between the novice and expert solution paths on these key processes.

Table 1: An overview of learner modelling techniques used to assess self-regulation in BioWorld.

SRL phase	Tool description	Learner modeling method	Data channels	Measures
		Implemented in BioWorld version 2.1		
Forethought	Evidence palette	Overlay method	Action attributes	Log file trace
		Under development for BioWorld version 3.0		
Performance	Library	Machine learning method	Action attributes	Log file trace
	Consult tool	Machine learning method	Linguistic attributes	Think aloud
Self-reflection	Case summary	Machine learning method	Linguistic attributes	Log file trace
	Feedback palette	Quantitative modelling	Affective/Motivational attributes	Self-report

We are using a data-driven approach that uses educational data mining techniques to redesign components of BioWorld's learner model. First, we have created a decision tree classifier that allows BioWorld to trace Novice library searches and infer whether the library topics explored leads novices to engage or disengage from the expert solution path. Data from the library classification model stands to improve instruction through the recommendation of specific topics in the library. Second, we examined the novice think-aloud protocols and clustered them based on sequences of cognitive and metacognitive activities, outlined by the SRL model, that occur prior to asking for a consult in BioWorld. The cluster model allows researchers to tailor the content of hints delivered by the consult tool in response to different profiles of help-seekers.

Although these models targeted different aspects of task performance, the following tools are designed to support novices in reflecting about their own approach to solving the problem. We evaluated the written patient case summaries using a neural network classifier to assess disease type and correctness of diagnosis on the basis of linguistic features. We plan to broaden the scope of the text classification model to provide novices with feedback on the quality of case summary sections and instruction on text writing strategies. Finally, we expanded the scope of the SRL model by modelling the impacts of achievement emotions and goals towards attention given to feedback in BioWorld. The logic model allows the system to assess learner characteristics through self-report, and direct novices' attention to aspects of the feedback that are most often overlooked by learners with a similar profile of characteristics.

Developing a Community of Co-Regulated Problem-Solvers

BioWorld serves as a platform to develop a community of practice, using cognitive apprenticeship principles to deliver instruction that brings in expertise from outside the classroom to the learning environment. We involve expert medical instructors in the case creation and expert knowledge building by having them use CaseBuilder, an authoring tool designed to allow domain experts and researchers to modify cases and explore instructional activities. Expert problem-solving traces are collected using verbal protocols, and researchers create visual representations that converge multiple solution paths for the purposes of validating the case solution. Case scenarios are built with medical staff and the case solution is uploaded to the server database, which can be uploaded by novices while solving problems with BioWorld. In doing so, instructors can design cases to be solved by groups of novices in the classroom, teaching on collaborative strategies that are critical in regulating the progress of groups and teams of problem-solvers. Recent advances in conceptualizing the context-specific nature of SRL, focusing on group collaboration, stands to better guide instruction (Järvelä & Hadwin, 2013; Volet, Vauras, Khosa, & Iiskala, 2013). Future research will evaluate the effects of adding new components to the BioWorld user model in terms of co-regulating processes involved in solving problems.

Supporting Self- and Co-Regulation in Intelligent Tutoring Systems to Help Students Acquire Better Learning Skills

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Providing scaffolding to help students regulate their learning has become an increasing focus within educational technologies, and specifically, within ITS. Overall, there is compelling evidence that scaffolding students' SRL can improve their learning gains (Aleven & Koedinger, 2002; Holmes, Park, Day, Bonn, & Roll, 2013; Wood and Wood, 1999). In this presentation we aim to extend the theory of SRL scaffolding in ITS by identifying three important developments in this area. First, we focus on the *objectives* of scaffolding. While domain learning remains an important objective, a more ambitious goal is to help students acquire better SRL skills and attitudes. Thus, the scope of the desired effect should extend beyond the supported environment and associated post-assessments to new learning situations. Second, we focus on the *role* of the scaffolding. Traditionally, the discussion around self regulation in ITS is framed either in terms of students' self-regulation (Winne, 1996), or external-regulation by the environment (Azevedo, Moos, Greene, Winters, & Cromley, 2008). However, learning in ITS can also be viewed as the emerging outcome of negotiations and interactions between learners and the system. We discuss this perspective in terms of co-regulation (Hadwin, Järvelä, & Miller, 2011), and investigate its implications on the design of regulatory scaffolding. Last, we discuss the *form* of the scaffolding, where we identify grounded feedback uses (Nathan, 1998; Stampfer & Koedinger, 2013) to implicitly encourage students to monitor their progress.

We ground the discussion on the objectives, roles, and form of SRL scaffolding by focusing on three important families of SRL strategies: Help seeking and help giving (Roll, Aleven, McLaren, & Koedinger, 2011; Walker, Rummel, & Koedinger, 2011); self assessment (Long & Aleven, 2013; Roll, Aleven, & Koedinger, 2011); and planning and monitoring (Holmes et al., 2013; Kinnebrew et al., 2013; Stampfer & Koedinger, 2012). In conclusion, we argue that these developments enable new modes of SRL support that could lead to sustained improvement in students' learning skills and attitudes.

From Domain Learning to Metacognitive Learning

As mentioned above, several successful examples show that students who receive relevant support for their learning *processes* demonstrated better learning *outcomes.* However, can we aim higher than that? Can support for SRL achieve the ambitious goals of helping students learn to regulate their learning, and thus become more competent learners?

We previously proposed a hierarchy of goals for SRL scaffolding (Koedigner, Aleven, Baker, & Roll, 2009). Support for SRL should first help students apply better learning behaviours within the supported environment. Second, it should lead to better domain learning outcomes within the supported environment. Third, students should demonstrate better SRL behaviour in a future learning event without the SRL support. Last, the support should lead to improvement in future learning outcomes without the SRL support.

In recent years, several studies have looked at transfer of SRL behaviours, allowing us to evaluate characteristics of SRL support that seek to improve future learning. Roll et al. (2011) gave students adaptive feedback on their help-seeking actions in a geometry tutor. They found that students who received feedback transferred better help-seeking skills to new topics within the same environment, when no support was offered, but not to a new (paper) environment. Long & Aleven (2013) found a similar pattern. After each problem in an

ITS on linear equations, students were prompted to assess their understanding. While these students demonstrated more productive learning behaviours on subsequent problems within the tutored environment, they did not transfer their improved self-assessment behaviors to a new environment. Limited transfer of improved SRL behaviours was also found in environments that support planning and monitoring. In these environments, SRL support for some components of the task led to improved SRL on other, unsupported, elements, but so far failed to show significant improvement on SRL strategies in transfer topics, even within the same environments (Biswas et al., 2009; Holmes, 2013). Thus, while well-designed SRL support can lead to transferable results, the patterns of transfer across tasks, topics, and environments should be further examined.

From Self- to Co-Regulation

To date, most efforts to scaffold SRL in ITS have focused on explicitly directing students to apply prescribed strategies, mainly through the use of static support. In such cases, regulation of learning could be considered Externally Regulated Learning (ERL; Azevedo et al., 2008), as the system chooses the sub goals and strategies for the student (e.g., using self-explanation prompts).

While the constructs of SRL and ERL are useful for discussing learning either from the student perspective (SRL) or the system perspective (ERL), they are somewhat less relevant when the regulation emerges from negotiations between the student and the system. A similar debate in regulation of groups sparked the idea of co-regulation (Hadwin et al., 2011). Here, we would like to extend the use of co-regulation to describe ITSs where the learning process emerges from negotiations and interactions between the learner and the environment. A good example for that process is the Open Learner Model (OLM; Long & Aleven, 2013; Zapata-Rivera & Greer, 2002). In OLMs, learners can view the ITS's estimation of their skills. Furthermore, several examples of OLM engage students in a discussion over desired goals and future activities. Another example is the work on peer tutoring (Walker et al., 2011). Rather than defining the interaction process for the student, the ITS offers strategies but does not impose them. The actual learning process is the result of contributions by the ITS and the two students who engage in the learning process. We argue that considering SRL support as a process of co-regulation can inform the design of support mechanisms that give more agency to learners and create stronger partnerships between ITS and the students.

From Explicit to Implicit Support

While many theories of self-regulation emphasize monitoring and reflection as key components of learning, students often fail to engage in these processes. One reason may be the failure of many ITSs to provide meaningful opportunities for student reflection. For example, when asked to calculate standard deviation of certain data sets, or to add two fractions, how can students know whether their answers are correct? Grounded Feedback supports triangulation, as the student can recognize the correct or incorrect application of a to-be-learned skill by evaluating the system response in alternative, familiar representation (which could be situational., visual., or based on already mastered procedures; cf. Natahan, 1998). We demonstrate this process using two environments: a fraction-addition ITS that uses graphical representations to help students evaluate magnitude, and a data-analysis ITS which uses contrasting cases to give students a baseline with which they can make intuitive predictions.

While Grounded Feedback allows students to monitor their performance, recent classroom experiments suggest that this approach is met with only limited success (Stampfer & Koedinger, 2012). A more powerful support may combine Grounded Feedback with explicit feedback on students' use of that information to assess their performance. Such feedback follows an intelligent novice model, or "immediate + 1" feedback, as feedback is suppressed when students commit domain-level errors (giving them a chance to detect their own errors), and is given when students fail to use the grounded clues to successfully make sense of their domain-level mistakes (Mathan & Koedinger, 2005).

To summarize, we identify three developments in the landscape of SRL support in ITS. Put together, we believe that SRL scaffolding should aim for co-regulation by involving students in the pedagogical decisions, and giving students opportunities to monitor their progress. At the same time, the ITS should, like a skilled human tutor, intervene when students are off track. These directions could lead to SRL scaffolding that is more responsive to students' interactions with the environment, gives students more agency over their learning process, and subsequently, may lead to sustained gains to students' SRL skills and attitudes.

From the Classroom to Industry: The Push for Intelligently Guided Self-Regulated Training to Support Complex Skill Development

Benjamin Goldberg, Robert Sottilare, U.S. Army Research Laboratory

The culture of education and training is quickly shifting. Technology is being utilized in the classroom more than ever, with new tools and methods completely reshaping how people interact with learning content and materials (i.e., interactive e-textbooks distributed to students on Apple iPads; Sloan, 2012). In turn, where people learn is also rapidly changing. With enhanced mobile networks that support on-the-go internet access and the availability of advanced light-weight portable computers, someone can conceivably learn and train from anywhere in the world. This is leading to a culture based around the self-regulation of learning, especially within industries like medicine and the military that value continual on-the-job training for skill development. In this context, ITSs are being defined as major focal points in regulating interaction and instilling metacognitive skills to support future training opportunities (TRADOC, 2011). This is based on empirical evidence in the learning sciences community showing the benefit of training metacognitive strategies and their subsequent impact on future learning outcomes (Koedinger, Aleven, Roll, & Baker, 2009; Poitras, Lajoie, & Hong, 2012; Roll, Aleven, McLaren, & Koedinger, 2011). The challenge is overcoming barriers linked to authoring such systems (Sottilare, Goldberg, Brawner, & Holden, 2012). At the current moment, authoring systems that support SRL is time consuming and requires expertise. Can tools and methods be employed to streamline the authoring of environments that take into account metacognitive functions?

From this perspective, there are two fundamental problems that must be addressed. First, military and industry training domains are extremely volatile in nature, with continual changes in task procedures as the result of advancements in technologies and techniques. With a change in task execution, an effective ITS must be able to accommodate shifts in procedural knowledge so as to continue providing efficient performance assessment and feedback. This needs to be accomplished without completely overhauling a system to account for new domain information. Next, with the role of the instructor being redefined in a SRL culture, there is a large burden placed on the student to regulate their training experience. This requires planning, executing a set of actions, monitoring and assessing performance, recognizing error, troubleshooting potential solutions, and identifying cause and effect as it relates to the context of the experienced problem (Zimmerman & Campillo, 2003). Especially with tasks that evolve over time, focusing instruction to improve cognitive processes and promote higher-order thinking, rather than improve task-specific procedures, is needed.

As such, research is required to identify streamlined processes that produce ready to use ITSs that are metacognitively aware outside of the laboratory setting. To further deconstruct these challenges, the authors will provide a comprehensive overview of the current gaps in ITS authoring that must addressed before training communities buy-in to adaptive training technologies. These include: (1) putting intelligent authoring tools in the hands of the instructor to create ITS-embedded training, (2) development of a systematic method of processes and standards to author such functions, and (3) providing sound pedagogical methods based on empirical evidence to enhance an individual's ability to regulate their own learning experience. These identified challenges will serve as the focal point of the discussion, where we examine current work surrounding authoring issues linked to SRL in post-academic training spaces and the role metacognition plays in pedagogical planning.

The Generalized Intelligent Framework for Tutoring (GIFT): Putting Authoring in the Hands of the Instructors

Authoring ITSs to aid in metacognitive development across training-based industries is a challenge that must be addressed. Training environments for military and industry relevant domains are often drastically different from the academic settings ITSs are typically applied within. Much of the training in job-related instances focuses on specific tasks and procedures that require proficiency before they can be fully conducted under proper operational contexts. In addition, how tasks are conducted depend largely on context, which is often ill-defined in nature. Thus, performing a task under one context may differ greatly from performing the same task under a different set of conditions. Therefore, a focus of instruction needs to be based on developing strategies to improve how individuals monitor performance, troubleshoot complications, and regulate attentional resources, rather than solely on executing task procedures. This will improve an individual's ability to self-regulate their future learning, as well improve how they conduct and adapt procedures based on reflections of actions taken.

The current issue is that building ITSs is expensive, labor intensive, and requires expertise across a number of disciplines (Murray, 1999; Sottilare, Goldberg, & Durlach, 2011). They are also commonly built as stand-alone solutions to a specific program, offering minimal reuse for future applications. Tools need to be developed that address these gaps and enable instructors to build and modify ITS model components that can be plugged into any training application available. This requires standardized methods and processes to build tutors from, along with an intelligently guided authoring process to assist instructors in building core components. Existing tools are available for standardized authoring of ITSs linked to cognitive example-tracing and constraint-based modeling techniques. These include Carnegie Mellon's Cognitive Tutor Authoring Tools (CTAT; Aleven, McLaren, Sewall, & Koedinger, 2006) and University of Canterbury's ASPIRE Authoring Tool (Mitrovic et al., 2008). They provide a generalized authoring environment, but lack elements linked to interactive simulation-based training systems such as gaming platforms commonly used in industry training.

The U.S. Army Research Laboratory (ARL) is currently addressing this problem. ARL is in the process of developing the Generalized Intelligent Framework for Tutoring (GIFT), an open source domain-independent architecture that provides standardized approaches for authoring, delivering, and evaluating ITS components and functions (Sottilare et al., 2012). Essentially, GIFT is a set of tools and standards used to author ITS solutions to promote and accelerate learning, regardless of the task being trained (Sottilare & Goldberg, 2013). What GIFT provides is a modular approach to ITS development, enabling a swap and play capability, which promotes reuse of standardized modeling techniques designed to accommodate any instructional domain. Where GIFT needs to shine is in compensating for the expertise and knowledge a particular author or instructor lacks. This requires tools that aid an author in modeling a domain to the parameters set forth by GIFT standards, developing assessments and triggers associated with the modeled domain, and identifying instructional strategies to utilize when triggers are activated.

The caveat is that all of these processes need to be defined in a generalized fashion so that they extend across domain implementations. Currently, GIFT monitors performance through an ontological representation of a domain by expressing objectives and concepts in a relational hierarchy. For each concept identified in the hierarchy, an assessment is authored that designates metrics linked to competency. These metrics are used to produce a learner state for each defined concept, which is used by the pedagogical model to inform guidance functions. From there, GIFT makes informed pedagogical recommendations on a domain-independent level (e.g., provide hint, provide prompt), leaving it to the instructor to author that strategy as an actionable tactic (Goldberg, Brawner, Sottilare, et al., 2012). In this instance, a developer authors multiple levels of tactics enabling the system to vary the level of detail provided in feedback messages based on individual differences associated with a learner. In the event that a system requires updates to task procedures, tactic definitions for each affected concept will need to be updated. This can be a taxing process on the course administrator if the task is modified on a regular basis. The same process can be said for supporting metacognitive tutoring. SRL behaviors require representation in GIFT's domain model that enables tracking of user interaction. This allows building rules to determine proper and improper execution. The goal would be to support the methods described above from the various authors. These determinations are used by the pedagogical model to enact a designated intervention; however, where metacognitive prompts differ is in their representation. They can be represented as standardized prompts that can be maintained across domains, without required edits.

Metacognition and Domain-Independency

As described above, GIFT works with system authors by providing instructional strategy recommendations, which are then translated into tactics as they relate to the training context. These tactics are used during ITS runtime and are selected based on a learner's individual differences. At the current moment, feedback in GIFT is domain dependent and requires explicit content linked to each concept modeled. When it comes to metacognitive feedback, what are the implications to a domain-independent approach? First, modeling techniques, such as the one presented in Biswas et al.'s paper, need to be developed to monitor an individual's practice of metacognitive strategies that can be expressed in a generalized format. Another example would be incorporating a help-seeking model, as highlighted in Koedinger et al. (2009). Researching and establishing models based around commonly available GIFT interactions (e.g., request hint button) can be used to build theoretical representations of how effective students use the interface to solve problems and troubleshoot errors. Depending on the domain, an assessment model will need to be generated that associates cognitive and metacognitive processes with task execution. This can be used to establish an assessment model for detecting learners exhibiting poor metacognitive behaviors, and is used to trigger feedback interventions to improve subsequent behavior. With support for applying varying modeling techniques, generic tactics can be identified that are based around effective metacognitive behavior, and should be based around learning theory identified by Roll et al. and Lajoie & Poitras. While tactics can be represented in a domain independent format, monitoring how a learner adapts their behaviors as a result of the intervention is an open question, and is dependent on the modeling approaches being applied.

In summary, we identify the desire from military and industry-based training communities to incorporate technologies to enable SRL. With technology being utilized more than ever for this purpose, using ITSs to monitor and improve metacognitive behaviors can greatly enhance the learning. To streamline this development, authoring needs to be taken out of the lab and put in the hands of those using the tools.

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