CONSIDERATIONS IN THE DEVELOPMENT OF AN ONTOLOGY FOR A GENERALIZED INTELLIGENT FRAMEWORK FOR TUTORING

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ABSTRACT

Tutoring research has been ongoing on since the 1960s and workable computer-based tutoring systems (CBTS) have been around since the early 1980s. Expectations are on the rise for CBTS to be available to the masses in much the same way that human tutoring is available from a variety of sources today. A limiting factor in the widespread use of CBTS is the cost to: author tutoring systems; author/deliver domain-specific instructional content; and assess the effectiveness of CBTS tools and methods. A structural framework to represent knowledge within the CBTS domain would enhance reuse and streamline processes making them easier to author on production line scale, and opening the entry point for CBTS to non-computer scientists. This paper considers the benefits and challenges in developing an ontology for a Generalized Intelligent Framework for Tutors (GIFT) to support the development of authoring, instructional and assessment standards and tools for CBTS.

Keywords: adaptive computer-based tutoring, ontology, frameworks, authoring, instruction, assessment

1. INTRODUCTION

In 2004, Loftin, Mastaglio and Kenny declared that "while one-to-one human tutoring is still superior to [computer-based tutoring systems] in general, this approach is idiosyncratic and not feasible to deliver to [any large population] in a cost-effective manner". This is still true today. A driving factor in the cost to author tutors, deliver instruction and assess tutor effectiveness is a lack of standard definitions, knowledge representations, data structures and processes upon which modular reusable tutor components could be built. This paper discusses the potential of a GIFT to make it easier and more cost-effective for large organizations meet their broad and diverse training needs.

Interest in adaptive CBTS continues to grow internationally. The North Atlantic Treaty Organization (NATO) Training Group's working group on Individual Training and Educational Development (IT&ED) found substantial instructional efficiencies (e.g., reduced costs and enhanced effectiveness) are readily achievable through the use of computer-based tutoring technology. However, most of the benefits examined concerned "memorization, understanding, and application of relatively straightforward facts, concepts, and procedures" and were not well suited to support complex or ill-defined environments where trainees were expected to apply judgment and exercise their adaptive and creative skills.

Expectations are on the rise for CBTS to adapt to each student's learning needs during instruction. The potential is evident, but unrealized for CBTS to skillfully facilitate student motivation, engagement, workload, and emotions in much the same way as expert human tutors "read" student behaviors and language to determine their readiness to learn and then employ strategies to maintain/enhance student learning experiences.

A common CBTS ontology would go a long way toward standardizing tutor authoring methods, management of instruction in CBTS environments, the assessment of student performance/learning during instruction, and the learning effect of tutoring systems, components and technologies (tools and methods). This paper assesses current trends in adaptive and predictive computer-based tutoring ontology development, identifies gaps and discusses opportunities for future research. The intent of this paper is to introduce CBTS ontology concepts discussed in the "adaptive and predictive computer-based tutoring" track of the the Defense and Homeland Security Simulation (DHSS) Workshop 2012 that are relevant to nations who wish to exploit technologies to support tailored and adaptive training solutions.

2. INFLUENCING FACTORS IN ONTOLOGY DESIGN

The Generalized Intelligent Framework for Tutoring (GIFT) is an open source tutoring architecture being developed by the U.S. Army Research Laboratory. The intent of GIFT is to develop/integrate CBTS capabilities to: 1) facilitate authoring, 2) manage instruction, and 3) assess learning and performance.

2.1. Facilitating Authoring

The design goals for authoring processes within GIFT are listed below and have been adapted from Murray (2003):

- decrease time and cost to produce CBTS
- improve usability and decrease expertise needed to produce CBTS

- incorporate good instructional design principles
- incorporate good human-computer interaction (HCI) design principles
- incorporate good instructional principles
- allow domain experts, system designers and trainers/teachers to develop, organize and use domain knowledge to author instruction
- allow for rapid integration of domain-independent knowledge (e.g., trainee data) and components (e.g., sensors, models, modules) to author a CBTS

To facilitate authoring, the GIFT ontology accounts for five core authoring processes to support rapid/economical development of tutoring systems and components. These processes support development of: user models; domain-specific knowledge; generalized (domain-independent) instructional strategies; human-tutor interfaces and; CBTS from components. While at the writing of this paper, not all elements within GIFT are fully matured, the ontology addresses their relationships and interactions.

2.1.1. Authoring User Models

In GIFT, user models include learner models (also known as trainee models), expert models, developer models and a variety of other models according to the types of GIFT users. In developing an adaptive CBTS, a comprehensive learner model (also known as a trainee model) is the basis for tailoring training (e.g., selecting domain-specific content based on the learner's competence level or selection of instructional strategies). There are two major challenges in deciding what needs to be in the learner model: identifying what learner information is relevant to instructional decisions; and collecting that information unobtrusively so as not to interfere with the learning process (Sottilare and Proctor, 2012).

Martens and Uhrmacher (2004) defined the learner model as consisting of a learner profile and a representation of the learner's knowledge. We have adapted and expanded this learner model (LM) to be represented by learner states that include the learner's cognitive and affective states as well as their potential and performance:

LM = {*potential, performance, cognitive, affective*} (1)

Potential is a measure of expected capabilities (or competence) based on the learner's historical data and their current performance. Performance is a measure of progress toward learning goals. Cognition and affect have been included in the learner model to address variables like engagement, workload and motivation which have a significant influence on learning. The learner states may be derived using computation or classification methods based on source data including data input (e.g., surveys), data capture (e.g., physiological or behavioral sensors) and historical data (e.g., learning management system records).

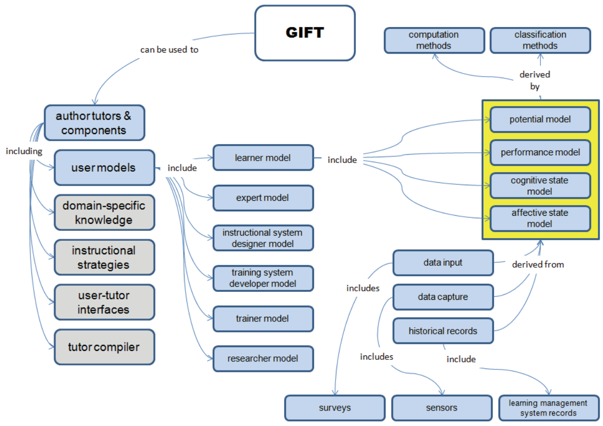

Figure 1: Authoring User Models

There are currently no standard learner models and this is a source of significant debate regarding what should and should not be included. The GIFT learner model presented above provides a flexible schema to allow changes in the future as research reveals which individual differences significantly influence learning outcomes. Ideally, a standard model would enable ease of integration by external user databases like Learning Management Systems (LMS).

It is envisioned that GIFT users will also include researchers, domain experts (also known as subject matter experts), instructional system designers, training system and courseware developers, and trainers. In this context researchers include personnel using GIFT to answer a research question and test a hypothesis, but we also include evaluators in this category, because they are also attempting to answer a question regarding the effectiveness of a component, method or system. The processes for assessing effectiveness are described later in this paper (see Section 2.3).

Domain experts are GIFT users who perform training tasks in a controlled environment and support the generation of expert models through the capture of their behaviors and decision processes. While operationally savvy, these experts may or may not have the experience needed to develop expert models on their own and must be guided by GIFT. Methods are needed to automatically capture expert behavior, feedback, decisions and reflections to construct the expert model. It may be necessary to capture data from several experts to insure a stable model. The ontology should include considerations to be adaptable to the needs of the domain expert as a user.

The same can be said for other users (instructional system designers, training system developers and trainers). Templates or user profiles will be needed to support the specific tasks conducted by these users and as for all users, the ontology should be capable of adapting to the needs and limitations of these different classifications of users.

2.1.2. Authoring Domain-Specific Knowledge

The selection or development of domain-specific knowledge should be informed by good instructional system design principles. An example includes the ADDIE model (Branson, Rayner, Cox, Furman, King, Hannum, 1975). The domain-specific knowledge discussion below is supported to a large degree by **Figure 2**. Domain-specific knowledge includes the following elements: learning objectives, media, task, conditions, performance standards, measures, common misconceptions, and a library of context-specific feedback and questions. In part, expert models inform tasks, conditions, the setting of standards, the selection of measures of performance, and common misconceptions (areas where learners are likely to have difficulty grasping domain concepts).

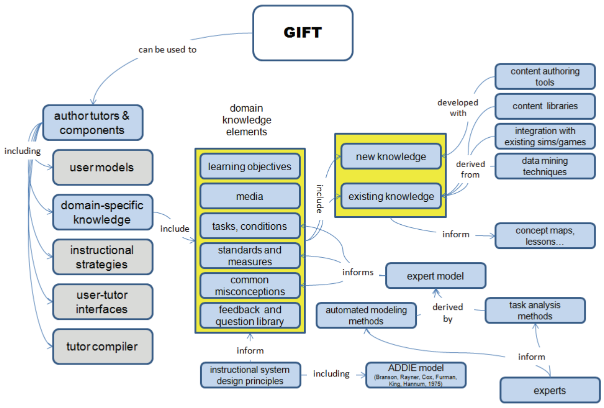

Figure 2: Authoring Domain-Specific Knowledge

A significant reduction in development time and cost might be realized by enhancing processes to reuse existing domain-specific knowledge. For instance, the cost of media development could be drastically reduced through the use of commercial games (e.g., game-based tutoring) and data mining could be used to locate appropriate shareable content objects (SCOs) on the internet to meet course development needs. SCOs may also be stored in local or server-based libraries.

If reuse is not an option, authoring tools, processes and templates are described in the ontology to support development of new knowledge. Authoring tools should be adapted to support the selection of media (e.g., interactive multimedia instruction (IMI) levels). IMI review checklist (U.S. Training and Doctrine Command Pamphlet 350-70-2, 2003) details media selection and interactivity.

2.1.3. Authoring Instructional Strategies

The search continues for a set of domain-independent strategies that will provide the optimal mix of direction and support to enhance learning and performance. Instructional strategies, tactics and strategy selection methods being evaluated for use in GIFT are based on a mix of motivational, tutoring and learning theories as shown in **Figure 3**.

Motivational theories like Maslow's hierarchy of needs (1943) are being analyzed to determine how the tutor can optimally capture the learner's interest and maintains it throughout the tutoring experience and subsequent interactions with the tutor.

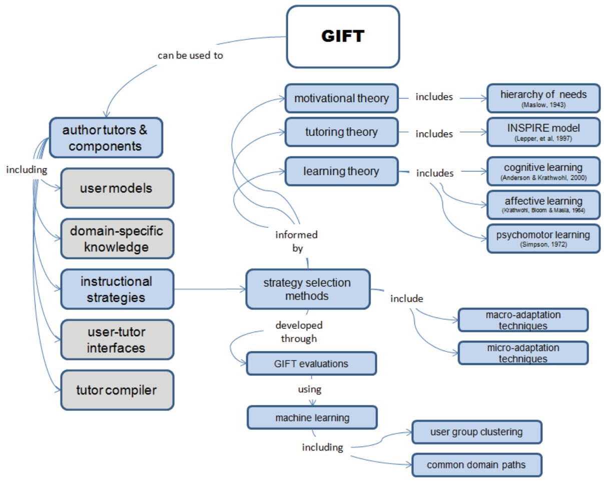

Figure 3: Authoring Instructional Strategies

Maslow addresses motivational concepts that are relevant to learning and include social (e.g., belonging) needs, self-esteem (e.g., confidence) needs, and self-actualization.

With the objective of emulating the characteristics of the best human tutors in our CBTS, we selected tutor studies conducted by Lepper, Drake and O'Donnell-Johnson (1997) offered the most promise. Their INSPIRE tutoring model is now the subject of an empirical evaluation that will be conducted using the GIFT experimental methodology outlined in Figure 4. This methodology is discussed in more detail in Section 2.3.

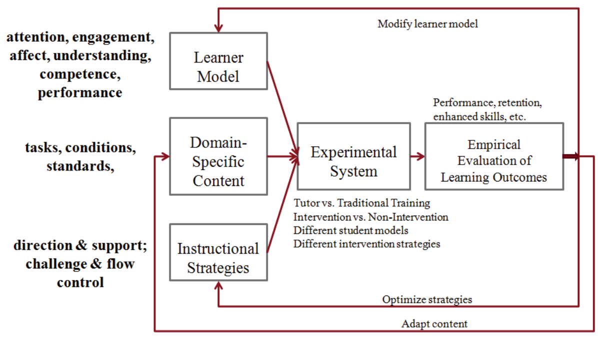

Figure 4: GIFT Experimental Methodology

Currently, strategies are being examined that align with the class of learning (e.g., cognitive, affective, psychomotor, social, and hybrid learning) highlighted in the instructional material. In the near-term, GIFT will be focused on two major techniques to adapt experiences to the needs of the learner: macro-adaptation and micro-adaptation. Macro-adaptive techniques use historical learner data (e.g., domain performance, competency level and experience) to understand learner potential and make appropriate instructional selections (e.g., challenge level of instruction) prior to the start of instruction. Micro-adaptive techniques use current cognitive and affective states to make near-real-time decisions about instruction and feedback during the tutoring process.

2.1.4. Authoring User-Tutor Interfaces

In order to support instructional strategies, the tutor must have access to data about the user (e.g., learner, expert, and researcher). This data may come from a user model (e.g., historical data from a learner model) or it may be real-time data accessed through user-tutor interfaces (see **Figure 5**). User-tutor interfaces present sensory stimuli (e.g., visual media) and receive learner data through sensors that collect information about the behaviors and physiology of the user. Two-way communication interfaces use artificial intelligence techniques to understand and generate natural language responses.

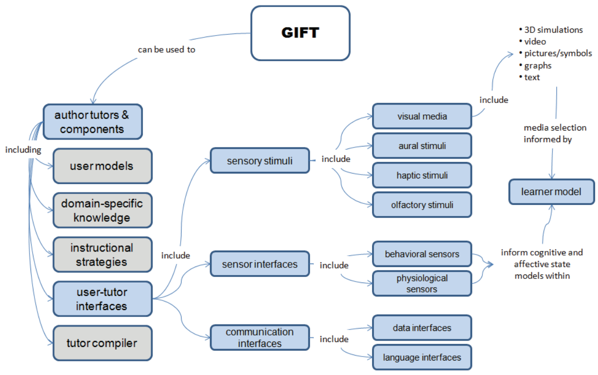

Figure 5: Authoring User-Tutor Interfaces

2.1.5. Integrating Tutor Components

An essential part of the ontology is the capability to integrate domain-dependent (e.g., domain knowledge) and domain-independent components (e.g., sensors, classification models and an instructional strategy engine) to compose a tutor for training or experimentation. As shown in **Figure 6**, GIFT system recommendations (heuristics) are informed by literature reviews and empirical research results and these in turn inform the selection of tutor module elements (e.g., clustering and classification models). The selection of trainee classification models are significantly influenced by the selection of sensors (behavioral and physiological).

2.2. Managing Instruction

This section reviews the initialization, pre-instruction, instruction, and post-instruction processes under consideration in a GIFT ontology.

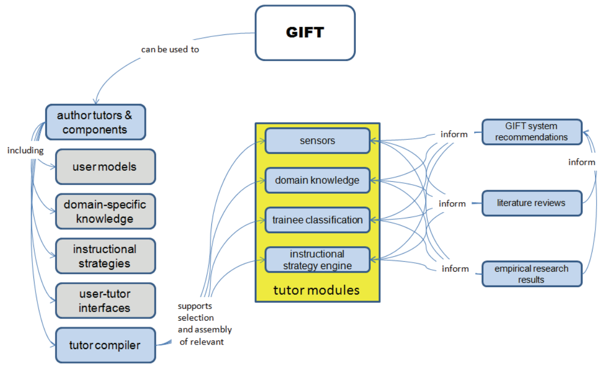

Figure 6: Tutor Compilation

2.2.1. Initialization and Pre-Instruction Phases

During the initialization phase, the user is authenticated and classified either as a learner, designer, developer, trainer or researcher. If the user is a learner, the learner model is initialized and used to inform domain knowledge selections and initialization of domain-independent modules (e.g., instructional strategy engine) within GIFT. Sensors are also initialized and verified to insure that data is being recorded. Once initialization is complete, pre-instructional activities can begin. Pre-instruction activities include pre-training surveys and a mission briefing that consists of a narrative (text or aural) to provide context and motivational support.

2.2.2. Instructional Phase

The instructional phase includes elements of the tutoring process and tutor behaviors as shown in **Figure 7**. The INSPIRE model of tutoring (Lepper, Drake and O'Donnell-Johnson, 1997; Lepper and Woolverton, 2002) is one model that could be used to moderate the CBTS decisions and feedback during instruction.

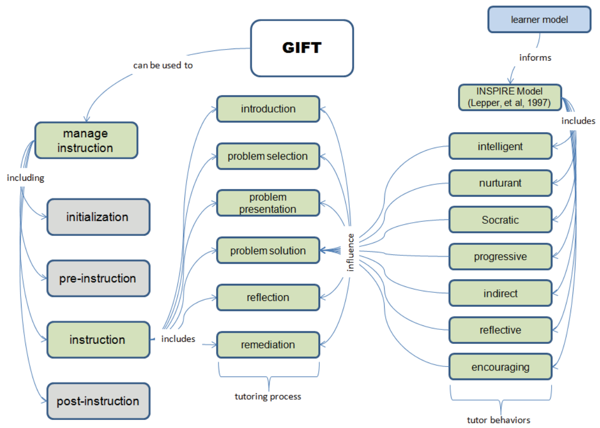

Figure 7: Tutoring Processes and Tutor Behaviors

Particular attention is paid to how tutor behaviors influence the five stages of the tutoring process. The introduction is an opportunity for the learner and the tutor to build rapport as the tutor demonstrates credibility and supportiveness by providing relevant historical information and motivational narrative.

During problem selection and presentation, the tutor also demonstrates its understanding of the problem difficulty, common misconceptions and other domain-specific knowledge to work hand-in-hand with an understanding of the learner's potential (e.g., domain competency).

During problem solution, the tutor monitors the learner's progress against expectations derived from the potential model within the learner model. Once the problem is solved, the tutor encourages the learner to reflect on the problem solving process, implications for use of this process in the future, and development of generalized models to solve similar problems. Finally, when necessary, the tutor provides ties back to foundational material to clarify misunderstood concepts.

2.2.3. Post-instruction

Once a body of instruction (e.g., a lesson) has been presented and concepts within the instruction have been mastered, the tutor begins a post-instruction process that includes a reaction assessment (what the learner thought of the training), a learning and performance assessment (to determine change in potential for future training), meaningful feedback to the trainee on their performance and their ability to generalize what was learned.

2.3. Assessment

Any CBTS ontology should be able assess improvements in learning and performance for any course or instructional subset (e.g., lesson or concept). This may be accomplished through frequent testing opportunities, but also may be assessed through other measures. For example, concept maps of the lesson could be used to delineate optimal paths based on expert modeling. For GIFT, we intend to use Markov Decision Processes to determine 'reward values' as the learner moves through each lesson and masters each concept. Increases in reward values will indicate learning while decreases in reward values will indicate potential misconceptions. The tutor will use this information in making decisions on how to bring the learner back to a learning path with a successful outcome.

The ontology should consider not only the learner performance, but also enable the assessment of tutoring methods and models across populations, and their effect on learning. For example, one research question that might be evaluated in GIFT is: what is the optimal set of variables that need to be represented in a learner model in order to make the most accurate predictions of learner states and thereby select optimal instructional strategies? To answer this question a number of variables (e.g., domain competency and historical performance) may be evaluated for their influence on learner state (e.g., cognitive or affective state) predictive accuracy using the experimental methodology outlined in **Figure 4**. Tutoring methods can also be evaluated using these methods.

3. DISCUSSION

The basis for a comprehensive CBTS ontology exists and has been evolving since the first CBTS were built over thirty years ago. The design objectives for authoring functions for CBTS are well documented (Murray, 1999; Murray, 2003; Koedinger, Aleven, Heffernan, McLaren, and Hockenberry, 2004). In addition to those frameworks already mentioned in this paper, there are several CBTS frameworks which have been proposed to address niche instructional design areas including: the evaluation of semantic knowledge during problem solving (Fournier-Viger, Nkambou, and Mayers, 2008), integration of tutoring approaches into existing collaborative applications via scripting (Harrer, Malzahn, and Wichmann, 2008), knowledge acquisition management (Riccucci, Carbonaro, and Casadei, 2005), and modeling human teaching tactics and strategies (du Boulay and Luckin, 2001). However, no framework to date has provided a comprehensive architecture to support authoring, instruction and assessment of CBTS.

What has been lacking is a methodology to assess tutoring technologies (tools and methods) and a framework to bring together best tutoring practices for authoring and instruction based on empirical experimental results. GIFT is our attempt at providing this holistic view of the CBTS problem space.

3.1. Current Trends

Few CBTS frameworks support multiple instructional approaches applicable across multiple instructional domains/topics. Most tutors employ a single strategy in a single instructional domain. AutoTutor broadly applies instructional strategies that include assessment/management of affective states (e.g., confusion and frustration) toward the goal of enhanced learning in well-defined domains (e.g., mathematics and physics). Affective learning influences how individuals manage their cognitive resources so applying strategies to enhance motivation encourages behaviors of perseverance and enthusiasm to continue when challenge is present.

3.2. Gaps

It will be critical to build upon AutoTutor's affective capabilities and extend tutoring into ill-defined domains (e.g., negotiation tasks and exercising moral judgment) experienced by military members in today's complex world. Ill-defined domains complicate the task of authoring CBTS since the linkage between specific learner actions and progress toward learning objectives is not always clear. Authoring is further complicated by the fact that there may be many more "paths to success" in ill-defined domains than in well-defined domains. This expands the number of scenario adaptations needed to represent all the possible (or likely) domain paths and increases the burden on scenario developers to provide instructional content at each node in the scenario.

In addition to being able to provide automated instruction to learners experiencing training in ill-defined tasks, researchers today are seeking capabilities to support low-cost, unobtrusive sensing of learner data (behaviors and physiological measures) to inform the cognitive and affective state classification models to determine learner states. This is an important element of the learning effect chain (**Figure 8**) where the outputs of cognitive and affective learner state models inform the selection of optimal instructional strategies to support higher learning gains (e.g., enhanced knowledge acquisition, skill acquisition, and retention). Improving the accuracy of instructional strategy selection may also be one path to accelerating learning (acquiring the same learning effect with less instructional contact time).

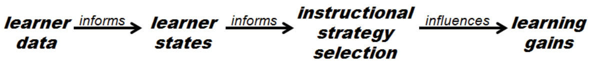

Figure 8: Learning Effect Chain

4. FUTURE WORK

GIFT will continue to evolve along the three primary vectors of authoring, instruction and assessment. Our intent is to provide GIFT as a set of tools, methods and heuristics to the user community and encourage open development that can be evaluated for inclusion in the baseline for the benefit of the user community. Research projects within the U.S. Army Research Laboratory will continue to focus on the assessment and validation of models and methods for inclusion in the GIFT baseline.

Several XML-based configuration tools are being developed to enhance the authoring capability and usability of GIFT including a learner modeling tool, a survey authoring tool, a domain knowledge file authoring tool, an event reporting tool, and experimentation support tool.

GIFT is evaluating other CBTS constructs to leverage open-source and government-developed capabilities. AutoTutor, AutoTutor Lite (web-based version of AutorTutor), and the Student Information Models for Intelligent Learning Environments (SIMILE) are three capabilities currently being assessed for inclusion in the GIFT baseline. AutoTutor and AutoTutor Lite manage tutoring experiences in multiple well-defined knowledge domains (e.g., math or physics). Additional research is needed to expand CBTS capabilities to support more ill-defined training domains (e.g., exercising moral judgment).

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