Effective Learner Modeling for Computer-Based Tutoring of Cognitive and Affective Tasks

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ABSTRACT

One-to-one human tutoring has been shown to produce the highest levels of learning effectiveness. Expert human tutors have the natural ability to assess and adapt to a learner's state (e.g., cognition and affect). As the tutor-learner relationship increases, human tutors are ultimately able to predict the learners' performance and behavior in future instruction. This natural sensing is hard to represent computationally. Although equipping computer-based tutoring systems (CBTSs) with such capabilities is an extremely complex problem, it is achievable. According to VanLehn (2011), the performance effect size (Cohen's d = 0.76) of simple, step-based CBTSs is as nearly as effective as expert human tutoring (d = 0.79). However, the performance gap widens as the level of instructional granularity increases (substep-based CBTSs: d = 0.40).

There is a strong motivation (as outlined in the Army Learning Concept for 2015) for CBTSs and other adaptive training technologies to emulate the same benefits that can be produced on a one-to-one basis. Current computer-based training technologies, although distributed and available worldwide, cannot interpret the readiness of a Warfighter to receive instruction. By assessing learner's state throughout training, multiple aspects of a learner's readiness and performance can be explained and the system can adapt instruction accordingly. Such analyses can increase the explanation of future learner state predictions.

The purpose of this paper is to explore the elements of a multifaceted learner model that can be expanded beyond well-defined educational objectives and inclusive of ill-defined objectives, which are usually portrayed in military and other job-related training. This paper will focus on the following: (1) key components of such a model (including an outline of individual differences that are potentially most beneficial to learning and determinants of learners cognitive and affective states); (2) primary challenges of this type of learner modeling approach; and (3) benefits and practical implications for users of learner models.

ABOUT THE AUTHORS

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INTRODUCTION

The Army Learning Concept of 2015 (ALC 2015) outlines a growing demand for military training environments to be highly adaptable, distributed, and more effective than human instructors. Consequently, the military is looking to leverage Computer-Based Tutoring Systems (CBTSs) and other adaptive training technologies as an optimal solution for this requirement. CBTSs provide a means to individualize computer-based training through the application of artificial intelligence tools and methods. Traditionally, they use modeled representations of the domain and the individual being trained for the purpose of tracking the learner's progression against that of expert/desired performance. More modern CBTSs incorporate mechanisms to assess reaction to training, and monitor cognitive and affective states found to impact learning outcomes. This enables a CBTS to perform two functions: (1) it provides the ability to identify errors of execution in real-time and (2) it can determine an individual's readiness to learn and diagnose states commonly encountered in learning environments (i.e., boredom, frustration, confusion, anger, attention, etc.). This information is then used to inform pedagogical strategy selection and system adaptations. Such an approach uses cognitive and affective states experienced during training as a critical target for adaptation. A CBTS facilitates the learning process by interjecting feedback when appropriate and tailoring content to maintain proper challenge and motivation levels based on the learning needs of an individual learner.

In essence, CBTS research strives to replicate benefits associated with one-to-one instruction (VanLehn, 2011) by accounting for individual differences that affect how one learns. CBTSs can have a profound effect on future U.S. Army training practices. They ultimately enable tailored and individualized instruction in the absence of a live trainer, and emphasize the desired function of future training outlined in the ALC 2015. Modeling approaches are used to diagnose performance and state determinations for the purpose of recognizing deficiencies and causes for error. This information is used in conjunction with characteristics and attributes associated with the learner to identify the optimal strategy to execute within the training environment. Such characteristics and attributes can also be used to enhance assessments of future performance and state determinations.

Yet, for intelligent tutoring to be incorporated into commonly applied training applications, considerations for what an adaptive tutor should provide within the Army training context must be addressed. At the 2011 Interservice/Industry Training, Simulation, and Education Conference (I/ITSEC), MG Nick Justice (Ret.) spoke directly on this topic. In a panel discussion on the future of military training, he stated a Warfighter's tutor must: (1) have knowledge of the operational context being trained, (2) have mechanisms to monitor and adapt to learner fatigue and cognitive load, (3) allow Warfighter's to 'train as they fight,' (4) prepare the Warfighter to become their individual best, and (5) motivate social learning (Justice, 2011). These tenets highlight the desired function for an effective CBTS-driven training application.

However, there are a number of challenges associated with CBTS implementation in the military. The primary constraint pertains to the required costs, effort, and time for training development. Military operational systems and tactics are ever evolving and training practices are continually modified and updated. Maintaining up-to-date training with adaptive mechanisms is almost impossible when they stand as one-fit solutions to the application they are developed within. In addition, many of the tasks and procedures Soldiers train on are kinetic in nature and require scenario-based exercises to apply knowledge and skills across various settings and conditions. This requires a CBTS to be able to monitor interaction within dynamic open-world environments and tie actions to desired training objectives. Lastly, the use of mobile applications for training is also on the rise, and methods must be identified for integrating CBTS frameworks with Smartphone technologies

Based on a foundation of previous CBTS-related research, the Army is currently developing a Generalized Intelligent Framework for Tutoring (GIFT) architecture that will serve as an experimental testbed towards the development of the next-generation CBTS (see www.GIFTTutoring.org for more information). This system addresses three primary capabilities that are currently challenging researchers within the CBTS community:

- **Learner Modeling**: Interpret comprehensive knowledge of a learner and utilize this information for accurately assessing a learner's current and predicted state of readiness for instruction as well as performance;
- **Instructional Strategy Selection**: Adapt and optimize instructional strategies based on the learner's state, performance, and learning needs;
- **Authoring and Expert Modeling:** Provide authoring capabilities to allow even a novice to reconfigure the system for any training domain and any learner.

This paper is targeted to increase understanding of the components and complexities of the first capability listed above, Learner Modeling. In this paper, we discuss key learner characteristics (individual differences) that may be used to determine the learner's cognitive and affective states and thereby be used to select instructional tactics and influence learning. This paper also presents an ontology of a learner model structure that can be constructed within GIFT.

What is Learner Modeling?

The learner model, a core module of CBTSs, is a representation of the learner's current state of knowledge at any given time (Kassim, Kazi, & Ranganath, 2004). Ideally, the learner model would include information on the learner's individual difference characteristics, his/her past and current competency, performance, cognition, affect, behaviors, etc. The CBTS uses this information to adapt and customize instruction accordingly based on the learner's state (Kassim, et al., 2004). A learner model is also known as a student model, especially amongst the academic population.

Learner models can be built to recognize learner's solution paths (Conati, Gertner, VanLehn, & Druzdzel, 1997), evaluate learner problem-solving abilities or performance (Katz, Lesgold, Eggan, & Gordin, 1993), or describe constraints for violations made by the learner (Gonzalez, Burguillo, & Llamas, 2006). The most effective techniques for generating learner models (i.e., *Bayesian networks* (Ivon Arroyo, Tom Murray, Beverly Woolf, & Carole Beal, 2004), *belief networks* (Reye, 2004), *case-based reasoning* (Aamodt & Plaza, 1994; Gonzalez, et al., 2006), and *expectation maximization* (Ferguson, Arroyo, Mahadevan, Woolf, & Barto, 2006)) are computationally complex and expensive. Other cheaper alternatives, such as model-tracing, can only record what a learner knows, but not his/her behaviors and characteristics. Learner models are commonly classified based on their relationship to the expert's knowledge (i.e., overlay, differential, or perturbation models) (Kassim, et al., 2004), but can also be classified by their performing function (i.e., corrective, elaborative, strategic, diagnostic, predictive, or evaluative) (Self, 1988). First generation CBTS implementations primarily adapted instruction based on learner performance and current state of knowledge. Thus, these systems utilized learner models with corrective or elaborative functionality but lacked any strategic, diagnostic, or predictive capabilities (Abdullah, 2003).

Research Problem and Scope

Learner models with higher-level functionality can have a strong impact on the accuracy of learner state assessments thereby increasing the adaptability of the overall CBTS. However, equipping these models with the capability to interpret the comprehensive knowledge of an individual learner is extremely complex. Regardless of the classification, build parameters (objectives), and functionality of a learner model, the underlying two-part question remains: *what aspects of the learner should be modeled and how can we achieve the best possible levels of state and performance classification and predictive accuracy?* Increasing CBTSs understanding of a learner can foster higher levels of learning by optimizing instruction based on the learner's individual needs. Over the last 15 years, this issue has received increased attention. More studies are being conducted to investigate the elements of a learner that are most influential to learning outcomes and can potentially better explain his/her state of readiness. Primary sub-research areas include, but are not limited to: learner state, cognitive modeling, affective modeling, individual differences, behavioral and physiological sensing, and performance assessment.

Most of this research is conducted within academic populations (mainly K-12 education) and well-defined, domain-specific CBTSs. If an objective of learner modeling research is to be inclusive of adult learners of the military and other job-related training, validation on the transferability of previous research as well as the identification of other useful aspects of the learner that scale beyond academia is needed. Furthermore, while significant progress has been made within these areas, there is no standardization for developing a comprehensive learner model, especially one that is modular and flexible enough for reusability across multiple CBTSs, domains, and/or learner populations.

The purpose of this paper is to explore the elements of a multifaceted learner model that can be expanded beyond well-defined educational objectives and inclusive of ill-defined objectives, which are commonly portrayed in military and other job-related training. This paper will discuss the following: (1) key components of such a model (including an outline of individual differences that are potentially most beneficial to learning and determinants of learners cognitive and affective states); (2) primary challenges of this type of learner modeling approach; (3) benefits and practical implications for users of learner models; and (4) suggestions and guidelines for future research and development.

ESSENTIAL ELEMENTS OF COMPREHENSIVE LEARNER MODELS

The content within learner models is generally categorized in two parts: *domain-specific* or *domain-independent* information [i.e. learner-specific characteristics (individual differences)] (Abdullah, 2003; Gonzalez, et al., 2006). Domain-specific information represents a reflection of the learner's state and level of knowledge or ability within a particular domain. This type of information primarily includes: historical competency (domain knowledge and skills measured over time), misconceptions, problem solving strategies, etc. Most learner models, particularly those of first generation CBTSs, are concerned with modeling this type of information because this allows the model to be more generalized across multiple populations. While this information is useful, it alone is not sufficient for providing the highly adaptive individualized training. Domain-independent information consists of all relevant characteristics of an individual learner and can include, but is not limited to, the following elements: learning goals; cognitive aptitudes; measures of motivational state; learning preferences (including styles and personality); interest; demographics; past performance and competency (non-domain-specific); behavioral/psychological measures; cognitive and affective dimensions; personal control beliefs (including general self-efficacy; locus of control); etc. These individual difference variables are significantly different between learners and, collectively, are not the same for any two learners.

Current learner modeling research is primarily centralized around understanding the influence of and interrelationship between domain-independent information (e.g., learner-specific characteristics) and how it can be best used in conjunction with the domain-specific information to optimally classify a learner state and performance. It is important to note that there is a separate, yet deeply interconnected, sub-area in CBTS research (i.e., Instructional Strategies) which also evaluates the influence of domain-independent information. However, this area focuses on how such information can impact the effectiveness or optimization of instructional strategy selection and learning outcomes. Obviously, both sub-areas are complementary to each other; however, the latter sub-area is not within the scope of this paper.

This section will discuss the key learner-specific characteristics that have been found to be influential to learning and are potential determinants of learners' states (both cognitive and affective) as well as learning outcomes. Additionally, this section will present other learner-specific variables that may be influential, but have not yet heavily researched within the CBTS community.

The Influence of Individual Differences

Gully and Chen (2010) identify four categories of intervening variables through which individual differences can have an impact on learning performance:

1. **Information-Processing Allocation**: Includes general cognitive ability, fluid and crystallized intelligence, and working memory capacity.
2. **Attention Focus and Metacognitive Processing**: Includes cognitive resources related pertaining to the learning ask or situation.
3. **Motivation and Effort Allocation**: Includes in general motivation (motivation to learn), as well as more specific motives such as learning goal orientation. Learners motivation and interest in learning task and environment are highly correlated with their engagement (Lepper & Woolverton, 2002)
4. **Emotional Regulation and Control**: Includes the processes involved in controlling negative emotional reactions (e.g. anxiety and frustration) and the generation of positive facilitative emotions during training. Emotional Intelligence is a key element of this mechanism and pertains to accounting for both personal (self-awareness, self-regulation, and motivational competency) and social (empathy and social skills) competencies (Goleman, 1995).

These mechanisms are targeted to be considered as part of the self-regulatory system (Gully & Chen, 2010). However, a literature review was conducted by the Navy to investigate and identify the individual differences that impact training outcomes in computer-based training (CBT). They advocate self-regulation theories can prove useful within an organizational context for observing how individual differences influence successful learning within CBT environments (Schultz, Alderton, & Bordwell-Hyneman, 2011), especially since such environments allow learners to have more control over their learning experiences (Sitzmann, Kraiger, Stewart, & Wisher, 2006). Like CBTSs, self-regulated learning models aim for the integration of cognitive, affective-motivational, and behavioral aspects of learning (Boekaerts, Pintrich, & Zeidner, 2000), and can be beneficial to describe various levels and processes involved in learning success, explain both mutual and recurring relationships established between these aspects, and directly relate learning with goals, motivation, and emotions (Boekaerts, 1999; Schultz, et al., 2011). Thus, there is a significant overlap between self-regulated learning models and the domain-independent information contained within CBTS learner models; this is a valuable factor to consider as CBTS learner models become more extensible beyond education and inclusive of different types of job-related training, such as military training.

Differences between social demographic variables, such as age, gender, race, educational backgrounds, etc. have been linked to multiple aspects of CBTS research. Arroyo, Murray, Woolf, and Beale (2003) investigated the influence of gender and cognitive differences on help effectiveness within an intelligent tutoring system (ITS). Multiple studies have investigated the influence of virtual tutors' appearances and personas on learning outcomes (Baylor, 2003, 2005; Baylor & Kim, 2004). While some general differences between demographical variables have been identified (for example, age could be indicative of generational trends or educational background/experiences could provide insight on how an individual learns and his/her motivation or goal orientations), demographic variables can demonstrate the best impact (as mediating variables) on cognition and affect when combined with other influential variables such as interest/motivation, attitudes/perceptions towards learning, self-efficacy, historical competency, or other individual differences variables previously mentioned. Learners' interest and motivation to learn pertains to their willingness, direction, intensity, and persistence of learning-directed behavior. It influences their choices during learning activities as well as cognitive engagement during instruction and training (Schultz, et al., 2011). The level of a learners' intrinsic motivation, goal-orientation, and need for achievement are also directly related to his/her overall motivation to learn and have been shown to be directly related to learning performance and other learning outcomes (Schultz, et al., 2011). Furthermore, learners' self-efficacy beliefs are also related to their motivation to learn, learning, performance, and job performance (Colquitt, LePine, & Noe, 2000) and have been shown to influence learners decision making during instruction and training (Brown, 2001). These aspects should be contained within the learner model structure; however, research assessing the influence of learners' motivational characteristics on outcomes and their relationships to other individual difference variables is practically non-existent.

The Navy's literature review specifies eight categories of individual difference constructs found as important predictors of training outcomes: motivation to learn; intrinsic motivation; metacognitive abilities; goal orientation; personal control beliefs; personality measures; organizational commitments and perceptions of fairness; and attitudes towards training (Schultz, et al., 2011). A significant contribution to the performance gap between computer-based and human tutoring lies in the ability of humans to naturally interpret and respond to learner's cognition and affective states (Carroll, Kokini, Champney, Sottilare, & Goldberg, 2011). A learner's "readiness to learn" primarily pertains to how cognitively and affectively he/she is prepared to receive instruction. To accurately classify a learner's state and performance at any given time, the learner model must have all-inclusive understanding of learner's cognition and affective states, influential individual difference characteristics, and performance.

Key Determinants of Cognition

Cognitive states that have been found to impact learning include: attention, distraction, drowsiness, engagement, flow, and workload (Carroll, et al., 2011). Learner-specific traits identified within CBTS learner modeling research attributing to explaining cognition for learning include: cognitive development (Arroyo, Beck, Schultz, & Woolf, 1999; Arroyo & Woolf, 2001) and metacognitive abilities (Schultz, et al., 2011); elements of Cognitive Trait Model (CTM) (e.g, working memory capacity, inductive reasoning ability, and divergent associative learning (Lin, Kinshuk, & Graf, 2007); and learning styles (Graf, Liu, Kinshuk, Chen, & Yang, 2009; Pashler, McDaniel, Rohrer, & Bjork, 2009). For clarification purposes, a "state" refers to a transitory characteristic of an individual whereas a "trait" refers to an enduring response tendency.

In many studies, learners' cognitive capabilities have been found to be a key determinant of their learning performance and other learning outcomes. Arroyo and Woolf (2001), suggest that students with low cognitive ability work better with highly interactive and concrete explanations, while students with high cognitive ability work more with symbolic explanations (Arroyo, Beck, Beal, Woolf, & Schultz, 2000; Arroyo & Woolf, 2001). This study used a computer-based development pre-test which is based on Piaget's notion of cognitive development (Piaget, 1953). Unfortunately, Piaget's theory can be used for identifying cognitive abilities of school-aged children, and is not suitable for assessing differences within adult populations. However, there are other cognitive ability pre-test assessments that can be utilized for adult learners and incorporated into learner models. Among the list of self-report measurable constructs for cognitive assessment include: The Need for Cognition Scale (Cacioppo, Petty, & Kao, 1984); the Visualizer-Verbalizer Questionnaire (VVQ) (Richardson, 1977); and the Mini-Mental State Examination (MMSE) construct (Folstein, Folstein, & McHugh, 1975). Each of these self-report constructs have been expanded and used within subsequent studies, but here are many other self-reportable constructs evaluating cognitive abilities.

Learners' metacognitive skills can also contribute to learner performance on top of their intellectual abilities. Veenman and Spaans (2005) found that metacognitive skills outweighed intelligence in predicting learning performance among secondary students. While intellectual ability accounted for 10 percent of the variance and metacognitive skills accounted for 17 percent of the variance, both predictors together accounted for 20 percent of the variance in learning (Veenman & Spaans, 2005). Metacognitive skills can be measured through both state and trait self-report constructs. Trait-based metacognitive abilities have been found to influence state-based metacognitive abilities. Furthermore, while metacognitive skills initially develop within separate knowledge domains, they become more generalized across domains (Schultz, et al., 2011; Veenman & Spaans, 2005). The benefit of understanding learners' metacognitive abilities/skills as part of the learner model is that such abilities are trainable and amendable before or during instruction within computer-based learning environments (Aleven & Koedinger, 2002).

A popular exemplar of a student model that accommodates learners' cognitive trait characteristics is the CTM. This model profiles learners' working memory capacity, inductive reasoning ability, information processing speed, and associative learning skills and has been found to be domain-independent as well as persistent over a long period of time. The model outputs as the role of a 'learning companion' which can be consulted by and interact with different learning environments. The performance-based model is not part of the CTM and is assumed to independently exist within the learning environment. However, the CTM does have a component called the Manifestation of Traits (MOT) Detector that uses information from the performance model as input. Although the CTM does not know any information on what the learner is learning, it provides information on how content can best be presented to a particular learner. More information on this model can be found in (Graf, et al., 2009). The individual traits embedded within the CTM are important learner characteristics for determining learners' cognition; however, such a model could prove useful to embed within the learner model since it accounts for the interrelationships between these elements.

Learning styles, or cognitive styles, pertain to a learner's preference on the most effective mode of instruction. The Felder-Silverman Learning Style Model (Felder & Silverman, 1998), a common model incorporated in CBTS research, differentiates each learner according to four dimensions: active vs. reflective, sensing vs. intuitive, visual vs. verbal, and sequential vs. global. Each dimension is quantifiable since it is expressed by values between +11 to -11. Over the years, several adaptive systems have been developed to cater to student's learning styles: AHA!, INSPIRE, KOD, LSAS, TANGOW (citations outlined within (Kinshuk, Liu, & Graf, 2009)). Other studies have linked learning style dimensions to the Cognitive Trait Model with some success (Graf, et al., 2009; Lin, et al., 2007). A recent literature review of learning styles research has produced major controversy as to whether or not learning styles impact learning. Pashler, McDaniel, Rohrer, and Bjork (2009) found many problems with previous learning style instruments, theories, and practices and concluded that such measures are not meaningful or cost-effective for assessments or adaptive training purposes (Pashler, et al., 2009). Thus, when considered as part of a learner model, learning styles should be used as lightly-weighted learner preferences and not as concrete determinations for instructional strategies.

Key Determinants of Affect

Affective states that have been found to impact learning include: Anger/Frustration, Boredom, Confidence, Confusion, Fear/Anxiety, Joy, Motivation, Sadness, Shame, Surprise, Wonderment/Awe (Carroll,

et al., 2011). Individual characteristics identified as attributing to explaining affect for learning include: personality, moods, and emotions. These three elements are closely interconnected.
Within traditional education, criterion for academic achievement tends to change over time from factors of cognitive abilities to factors of personality and motivational variables (O'Connor & Paunonen, 2007). Thus, the impact of such variables on performance may be more influential for adult learners. The Big Five Model measures five dimensions of personality: extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience (McCrae & Costa Jr., 1992). Of the five factors, the conscientiousness dimension has been the most consistently associated with post-secondary academic success (O'Connor & Paunonen, 2007). Conscientious learners tend to be self-disciplined, goal-driven, and motivated to learn. Moreover, conscientiousness combined with previous performance and emotional stability assessments can be predictive of differences in performance over time (Schultz, et al., 2011).

Evaluation of personality is a relatively short and easy assessment in which results are consistent over a long period of time. Learners' emotions (affect) responses span a wide spectrum between negative and positive, tend to follow a pattern over time and situations, and can easily change within a short period of time. Within MG Nick Justice's (Ret.) address at I/ITSEC 2011, he highlights that interpreting and responding accordingly to Soldiers' range of emotions during training is especially important, as their emotional spectrum may expand further than the norm, depending on the learning task. Positive emotions can have a facilitative effect on intrinsic motivation and cognitive processes (Schultz, et al., 2011); thus, the ability to avoid and account for negative emotions (unless purposely caused) is crucial to learner performance.

Learners' emotions are also directly correlated with their moods (i.e., positive emotions = positive moods and negative emotions = negative moods). Whereas emotion tends to be more clearly identifiable, mood tends to represent more diffused and unfocused feelings of affect. Self-report measures of learners' emotions and moods, such as the Positive and Negative Affect Schedule (PANAS-X) Questionnaire (Watson & Clark, 1994), the State-Trait Emotion Measure (STEM) Scale (Levine & Xu, 2005), and the Self-Assessment Manikin (SAM) non-verbal pictorial technique (Lang, 1985) are typical methods for collecting emotional assessments during experimentation. However, such methods are not ideal during real-time training situations because they disconnect the learners' immersion and may provide invalid results. Over the past decade, CBTS learner modeling research has looked to affective computing and sensor-based technologies to ascertain classifications of learners' emotions during instruction. This presents one of the grand challenges outlined later in this paper.

Traditionally, emotion (affect) was not considered to be part of the cognitive process; however, research has shown that both emotion and cognition are closely intertwined (Picard et al., 2004). Although the determinants presented in the above are presented separately, CBTS research has found interrelationships these among learner-specific characteristics (as examples: personality and cognitive abilities [(O'Connor & Paunonen, 2007; Schultz, et al., 2011)] learning styles and cognitive traits (Graf, et al., 2009).

Future learner models can also benefit from other modeling research areas. Learner modeling is considered a subset of user modeling; therefore, aspects of user modeling research may be beneficial to future learner model development as CBTS expand to be inclusive of job-related training. The primary area of user modeling research pertains to users' acceptances and system interactions as determinants of their current and future system usage behaviors. Evaluated elements include: users' expertise, skills, attitudes, perceptions (i.e., perceived affinity, usefulness, and ease of use), and self-efficacy towards both computers in general and the specified system have been found to be indicative of users' usage behaviors and future usage intentions. Combined with the same perceptions toward learning, learner models could potentially increase explanation of states, performance, and system behavior. Little CBTS research has been done in this area; however, preliminary findings have shown that there is a significant relationship between learners' acceptances of pedagogical agents, or virtual tutors, embedded within a learning environment and the learners' acceptances of the learning environment itself (Holden & Goldberg, 2011). A prior study also identified links between students' behaviors with a tutor and their attitudes and perceptions (I. Arroyo, T. Murray, B. Woolf, & C. Beal, 2004).

GRAND CHALLENGES OF COMPREHENSIVE LEARNER MODELING

Only future research and validation will tell whether and how the learner-specific characteristics outlined in the previous section will fit within a standardized learner model and attribute to learners' cognitive states, affective states, and performance. While some of these elements are collected through self-reported measures, such measures, especially those collected during training, can break the flow and engagement of training. Thus, as previously mentioned, researchers are looking to physiological (i.e., GSR, EEG, ECG), haptic (sensitive mouse or chair), and observational (cameras, eye-tracking, etc.) sensors to develop real-time and predictive models/classifiers of affect and cognition. These classifiers can be used in conjunction with self-reports, historical data, and performance to provide optimal classifications (both real-time and predictive) of learners readiness to learn. Figure 1 presents the ontology of the derivations of a learner model structure based on historical data, self-reported data, and sensor measurements.

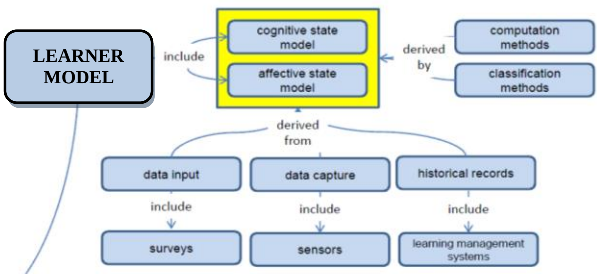

Figure 1: Ontology of the Learner Model Structure within GIFT

This ontology is used to develop the learner model of the GIFT system. The future functionality vision of this module within GIFT is outlined as follows:

Inputs:

- Weighted model/algorithm containing relevant and influential learner characteristics (Learning Management System [LMS])
- Processed sensor information (Sensor Module)
- Current performance and other assessment variables (Domain Module)
- Survey response data (Survey Authoring Tool)

Functions:

- Pre-training and Mid-training Assessments
- Readiness Monitoring (interpretation cognition and affect)
- Performance and Progress Monitoring
- Interaction/Psychomotor behaviors of trainee within the training simulation

Outputs:

- Changes of monitoring results (including potential elements contributing to change) (Pedagogical Module)
- Necessary updates relevant to trainee characteristics (LMS)

The pre-training assessments will establish the initial readiness levels and performance expectations which will be used for monitoring during instruction and mid-training assessments. The readiness monitoring will be initialized during/after pre-training assessments and will have the ability to identify and compare cognitive and affective state change to provide to the pedagogical module with the necessary information to adjust training and feedback as needed. The performance and progress monitoring will also be initialized after pre-training assessment and considers elements of domain competency and previous experience. It will also use the readiness monitoring to help explain changes in performance. Both types of monitoring will be comprehensive and consists of multiple views (i.e., previous, current, as well as short-term and long-term predicted with probability accuracy). This type of monitoring requires real-time and continuous assessments.

Real-time/Continuous Learner State and Performance Assessments

While is it clear that the learner model should include elements of population demographics, cognitive ability, personality traits, motivation, learning preferences, and historical background, the designer should not lose track of the purpose of the system. The purpose of the CBTS is to tailor training content in order to: a) reduce learning time, b) learn more material in the same timeframe, c) provide content relevant to the specific individual, or d) reduce teacher/classroom overhead costs (Woolf, 2011). As such, the most commonly measured attribute about the learner, either in a CBTS or an adaptive training system, is their performance. Computer engineering has now progressed to the point where monitoring the performance of the learner in real-time is not only possible, but is a relatively simple technical task. This is a critical step for the CBTS to diagnose problems in performance, and respond to them proactively (Brawner, Holden, Goldberg, & Sottilare, 2011; Person & Graesser, 2003). However, there is more information within performance measurements than the measurements alone. Just as sensor inferences of state can be used to predict performance, the performance measurements can aid in inferring state (Muldner, Burelson, & VanLehn, 2012).

Research shows that classification of affect is likely to be highly individualized (Baker, 2010). As an example, a generalized Bayesian system of classification for 5th grade students in North Carolina classrooms (Robinson, McQuiggan, & Lester, 2009) is not able to withstand validation testing upon a different class (Sabourin, Mott, & Lester, 2011). While a generalized model of affective and cognitive states may be difficult to construct, there is more than enough evidence to support the idea that they influence learning (Graesser & D'Mello, 2011). As part of this, the GIFT architecture (www.GIFTtutoring.org) has been designed to support real-time performance messages and the current and predicted cognitive/affective states. While very little is currently performed with the interfacing messages of predicted affective and performance state, it is a research question of significant interest, and known to be meaningful. Furthermore, in order for a learner model to be truly comprehensive, it would need to have various views of learners' states and performance. To avoid frequent reactions/responses that may not be necessary, learner models should be able to decipher between learners' short-term (current), long-term (predicted), and prior-term (previous) interpretations. This is to avoid frequent changes of instructional strategies solely based on short-term changes within state and performance.

Accurate Classification of Learner State

Combining and accounting for the interrelationships within and between learners' cognition, affect, and performance accurately can be overwhelmingly cumbersome. The above sections reference that a real-time model of performance, cognitive state, and affective state should be considered as portions of a learner model. While the real-time monitoring of performance is a relatively simple technical task, the use of real-time sensor data streams is technically complex. The first technical complexity is the individualized nature of affective responses (Baker, 2010). The second is the high variability of individual response due to sensor variations, placement, daily mood change, and mental state modulation (AlZoubi, Hussain, D'Mello, & Calvo, 2011). The third source of complication is the potentially infinite length, new evolution, and existing drift of state concepts within a data stream (Masud et al., 2010). These combine to make real-time learner models of cognition, affect, and performance arduous to construct.

BENEFITS OF LEARNER MODELING ACROSS MULITPLE DIMENSIONS

More and more, CBTS learner models are being used to inform tailored and adaptive instructional strategies to support higher learning gains, accelerated learning, and retention. The benefits of standardized learner models that can adapt instructional decisions across a variety of learning domains, tasks, and learning categories (e.g., cognitive, affective, psychomotor, social, and hybrid learning) is domain-independent processing and a higher degree of reuse. Standards enable instructors to translate and use existing learner data repositories to support long-term learner models, and enhance macro-adaptive tailoring decisions affecting both learning and retention (Sottilare & Goldberg, 2012).

Standards for sensor processing within the learner module facilitates the integration of commercial physiological and behavioral sensors to enable the processing of learner data by empirically evaluated algorithms that are "best in class" in determining learner states. A modular framework allows for flexibility in selecting the processes included in learner modules for a particular training session or experiment. In addition to data from repositories and sensor data, learner data may also include survey instrument data that can be used to determine learner states and traits, and then play a role in determining instructional strategies. Other variables of interest (e.g., learner working memory, learner competency, individual differences) in standardized formats facilitate integration of new/improved learner data processes.

An additional benefit of standardized, modular learner models is the opportunity to implement open learner modeling constructs where learners have insight into their progress and have a hand in shaping their learning experiences. Standardization means that learner data can be presented to the learner in a variety of formats (e.g., text feedback, graphics). For example, it may be useful to graphically show learner progress over time, or skill competency in comparison to expectations (standards). It may also be important to allow learners to determine sequencing of lessons based on their understanding of strengths/weaknesses as presented via learner modeling. Finally, it may also be important to allow learners insight into their thought processes (e.g., metacognition) to support development/analysis/restructuring of their mental models.

CONCLUSIONS

This paper provided an overview of essential elements to be considered for learner models of future CBTSs which are expandable to adult learner populations and military training. While much research is needed to investigate the transferability of previous findings, future CBTS researchers and developers should consider the following: model development and evaluation of few elements at a time to identify interrelationships between elements and their influences on learner state; controlled experimentation (including sensor validation and comparisons to self-reported data and user-experience post-experiment interviews); and increased collaboration and data sharing.

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