Designing Adaptive Computer-Based Tutoring Systems to Accelerate Learning and Facilitate Retention

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This article considers the premise that computer-based tutoring systems (CBTSs) could be used to accelerate learning and facilitate retention because of their ability to assess, predict and adapt to unique learner traits and states. Existing CBTSs tend to provide each learner the same instructional regimes (e.g., event-driven feedback) or provide very prescriptive instructional adaptations (e.g., change of flow or challenge level) based on the learner's progress toward objectives. Much like human tutors, the success of CBTSs relative to accelerated learning is predicated on their ability to maintain high learning states while minimizing states in which little or no learning is occurring (e.g., boredom, overstimulation, confusion, frustration). By considering accelerated learning principles (e.g., contextual relevance and social learning) in the designing CBTSs and by implementing methods to more fully model the learner and the learning context, tutoring systems should realize greater success in facilitating the learner's rapid development of comprehensive mental models and improved reasoning skills, while promoting a lasting effect (retention). This article considers accelerated learning principles, retention issues and individual differences as drivers in the design and development of an adaptive, computer-based tutoring capability.

KEYWORDS: Accelerated learning, Retention, Computer-based tutoring design, Adaptive tutoring, Tailored training

This article examines how accelerated learning principles could influence the design of computer-based tutoring systems (CBTSs; also known as intelligent tutoring systems) resulting in optimal self-directed learning experiences for learners. For the purposes of this discussion, accelerated learning is defined as any learning system that attempts to optimize time spent learning versus content learned. The goals of this approach are for faster attainment of knowledge and skill, and increased job performance with better retention of learning (Andrews and Fitzgerald, 2010). The motivation for examining technology (tools and methods) to support accelerated learning is higher throughput for large organizations such as the U.S. military where small reductions in time spent learning can result in large savings. The motivation to examine CBTS as an accelerated learning tool is to compound the opportunity to effectively support self-regulated learning and thereby reduce infrastructure (e.g., classrooms) and support (e.g., instructors) previously required to develop and deliver effective/efficient training.

This article addresses the influence of accelerated learning and retention principles on the design of CBTSs in one-to-one training contexts. Toward this end, we describe a core model for CBTS and introduce five CBTS design objectives that tie the influences of cognitive theories, expert human tutoring models and tailored instructional strategies to accelerate learning and enhance retention. The five objectives are: supporting efficient, tailored instruction through comprehensive student modeling; supporting active, case-based learning; dividing training content into manageable chunks; supporting reflection and social learning; and testing for understanding.

Furthermore, we discuss how our current CBTS architecture, the Generalized Intelligent Framework for Tutoring (GIFT) incorporates the five CBTS design objectives and enhances the core model for

CBTS. Finally, we provide recommendations for future CBTS research and development to support accelerated learning and retention objectives for individuals and teams.

Core Model of CBTSs

Before discussing the use of CBTS to accelerate learning, some common definitions for the functions of a CBTS are needed. Figure 1 illustrates a functional model of an adaptive individual tutoring system (Sottilare, 2010) which was derived from Beck, Stern and Haugsjaa's (1996) tutoring model.

As in most CBTS, the major components include a student model (also known as a learner, trainee or user model), an expert model, domain knowledge (including instructional content, questions, hints and misconceptions), a pedagogical module and a communication module. The student model contains information about the student's current performance (as determined by pedagogical agents and a set of standards), the student's domain competency (e.g., novice or expert), and sensor data (physiological and/or behavioral measures) used to ascertain the student's cognitive and affective states.

The expert model (also known as the ideal student model) contains standards to measure the progress of the student in the training domain as defined by the domain knowledge. The domain knowledge includes instructional content, problems, misconceptions, challenge levels and options for feedback. The pedagogical module assesses the student's progress based on interactions with the instructional content. It uses this information to determine which instructional strategies (e.g., direction, support, questioning, changing challenge level or pace of instruction) to employ during the training session. The communication module is the student's interface with the CBTS and includes devices for sensory interaction and data input (e.g., visual display, speakers, computer mouse, haptic devices for touch, keyboard for input) to present instruction, allow

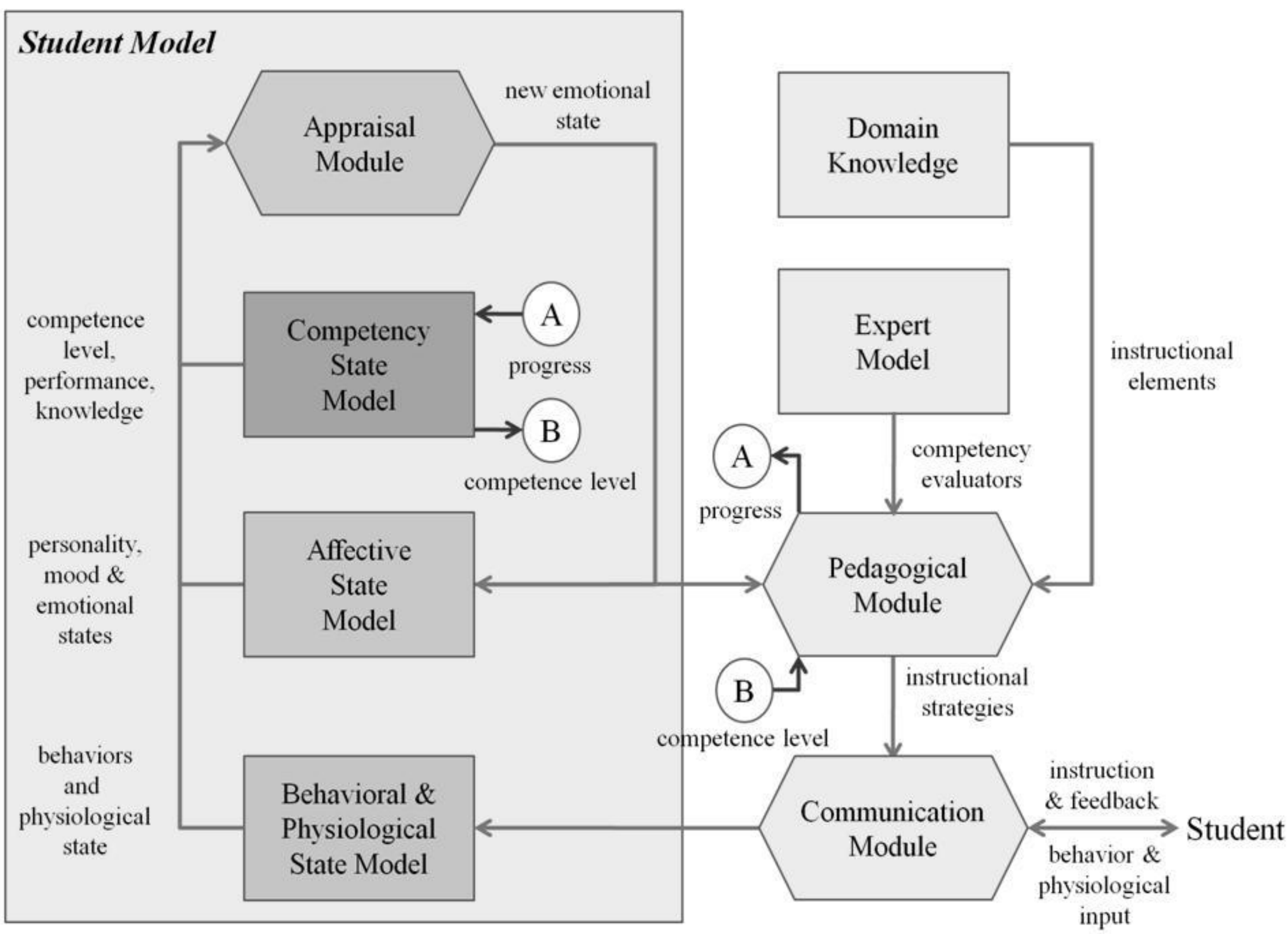

***Figure 1*. Adaptive Tutoring Model (Sottilare, 2010)**

interaction and provide feedback to the student. This article considers the design and interactivity of tutor components in supporting accelerated learning and facilitating retention.

CBTSs could, and we believe should, be designed for efficiency to support accelerated learning, but should not ignore the need to challenge the student in the interest of maintaining motivational level and facilitating retention of knowledge and skills. In other words, their design should maximize high states of learning (e.g., acquisition of knowledge, understanding and application of concepts) while minimizing/eliminating states where little or no learning is occurring (e.g., boredom, overstimulation, confusion, frustration). It is undesirable to totally eliminate frustration since some difficulty in learning can maintain challenge levels and aid retention (Bjork, 1994). In order to optimize learning efficiency, a CBTS must be capable of two critical functions: 1) the ability to sense and model the student's states (e.g., cognitive, affective) and 2) select instructional strategies (e.g., scaffolding) tailored to the student's states/traits and relevant to the learning context.

Sensing and modeling student states are critical to the computer-based tutor's selection of appropriate instructional strategies. Strategy selection is vital in maintaining the student in an optimal flow to accelerate learning. Human tutors do this through observation and intervention (e.g., questioning, supporting, directing) and often their historical knowledge of the student's learning habits. CBTSs would also interact with the student in this way, but additionally they would have the option to use physiological sensing technologies (e.g., electroencephalographs, galvanic skin response sensors and/or interbeat heart rate monitors), behavioral sensors and classifying methods (e.g., clustering techniques, decision trees or Bayesian algorithms) to ascertain their cognitive (e.g., level of engagement) and affective (e.g., emotions, mood) states.

For example, using the training context (where the student is in the training), an eye-tracker (behavioral sensor) and breathing monitor (physiological sensor) along with the student's progress, the tutor can ascertain the probability of a negative learning state (e.g., confusion, boredom, distraction or frustration). Based on the student's affective and cognitive states, their progress and the learning context, the tutor selects an appropriate instructional strategy and set of problems or cases to be worked, perhaps using a classification method (e.g., Dynamic Bayesian Networks or Partially Observable Markov Decision Processes). The cycle continues as the tutor interacts with the student, senses and classifies the student's states, and determines future instructional strategies.

To illustrate the elements of the core CBTS model, we provide an exemplar highlighting data inputs and interactions within a human-tutoring system. First, instructional material is presented to the student which may or may not elicit an emotional reaction (e.g., anger or frustration). Behavioral sensors (e.g., web camera) can be used to measure six distance measures on the student's face and algorithms can be used to assess the relationship between these facial distances and six universal emotions (sadness, joy, anger, fear, disgust and surprise) (Neji & Ben Ammar, 2007). Changes in the facial distances D1: the opening of the eye; D2: distance between the interior corner of the eye and the eyebrow; D3: opening of the mouth in width; D4: opening of the mouth in height; D5: the distance between the eye and eyebrow; and D6: the distance between the corner of the mouth and the external corner of the eye) are captured and stored in the student model. Emotional states are classified within the student model based on behavioral measures. The student's emotional state is then sent to the pedagogical module and used to influence the selection of tailored strategies (e.g., feedback, motivation, explanation, steering) to be implemented by the tutor.

However, using sensor-driven data along with performance metrics to trigger instructional interventions in a CBTS is not enough. Tailored strategies authored to accelerate and optimize learning outcomes must accommodate the learning sciences theories of cognition, and should be designed around considerations associated with experience, real-time performance and diagnosed states. Based on these variables, CBTS designers must understand how adaptive strategies should be leveraged to assist individuals with their strengths and weaknesses within a given domain.

Implications of Cognitive Theories in CBTS Design

Having reviewed the high-level architecture of CBTS, we can consider CBTS design to meet the accelerated learning objectives as derived from cognitive theories on accelerated learning. To this end, we review the fundamentals of the Cognitive Load Theory (CLT), the Cognitive Flexibility Theory (CFT) and the Cognitive Transformation Theory (CTT).

Cognitive Load Theory in CBTS Design for Accelerated Learning and Retention

CLT asserts that information should be presented in a manner that optimizes student performance by allowing instructional designers to manage the limitations of concurrent working memory load during instruction (Sweller, Van Merrienboer, & Paas, 1998). CLT defines three types of cognitive loads: intrinsic, extraneous and germane.

Intrinsic cognitive load pertains to the inherent difficulty (e.g., complexity, vagueness, interactivity) associated with the instructional content and is not controllable by instructional designers (Sweller, Van Merrienboer, & Paas, 1998). For example, an algebra tutor would weigh the difference in intrinsic cognitive load (also known as problem difficulty) between an addition problem and solving a differential equation. While instructional designers cannot control the difficulty associated with a specific problem (e.g., except through changes in the wording of the problem), they can address when to select another problem of greater or lesser inherent difficulty. It will be important for the domain knowledge within a CBTS to include an assessment of problem difficulty within any particular training domain. The pedagogical agent within a tutor would narrow the selection to problems of appropriate difficulty based on the recent and long-term progress of the student in that domain and perhaps related domains. For example, the short-term positive progress of the student might indicate that harder problems are needed to maintain a positive engagement level, but his long-term progress may indicate a slower gradation of increasing problem difficulty based on previous interactions with the tutor. By examining short- and long-term trends, the tutor can manage the student's arousal to maintain him in a "zone of proximal development" (Vygotsky, 1978; Csikszentmihalyi, 1990). Low arousal/challenge level can result in boredom and high arousal/challenge level can result in confusion or frustration. Defining the segmentation and sequencing of information within the domain knowledge may also be useful in managing intrinsic cognitive load.

Extraneous cognitive load pertains to the way information is presented to students, and can be controlled by instructional designers (Sweller, Van Merrienboer, & Paas, 1998). For example, a history tutor could describe Abraham Lincoln's mannerisms, or the tutor could provide a visual animation of Abraham Lincoln to illustrate his mannerisms. The written media might be more efficient and cheaper to produce, but might be more expensive in terms of extraneous cognitive load. As well, this load is at the expense of germane cognitive load, which facilitates learning.

Germane cognitive load is associated with schema that a student engages that contribute to attaining the domain learning objectives (Sweller, Van Merrienboer, & Paas, 1998). Pedagogical agents in CBTSs are responsible for managing germane cognitive load. The tutor design should account for methods that recognize cognitive load type (intrinsic, extraneous and germane) and minimize extraneous load while maximizing germane cognitive load.

As important as the management of cognitive load is in the design of CBTS, it is also necessary to address the need for flexibility and context in learning. To this end, we explore the Cognitive Flexibility Theory (CFT), which focuses on the nature of learning in complex and ill-defined domains (Spiro, Coulson, Feltovich, & Anderson, 1988).

Cognitive Flexibility Theory in CBTS Design for Accelerated Learning and Retention

CFT stresses the importance of how knowledge representations are constructed by the student so they can easily restructure domain knowledge later to adapt to changing scenarios by rejecting their simplistic understandings (Spiro, Coulson, Feltovich, & Anderson, 1988). CFT is especially applicable for presentation of instructional content by "interactive technology," a category that includes adaptive CBTSs (Jonassen, Ambruso, & Olesen, 1992). The following tenets of CFT may inform the design of CBTSs: multiple representations of instructional content; context-dependent knowledge; complex, case-based instruction; and interrelated knowledge representations.

Computer-based tutor design should allow for multiple representations of instructional concepts and learning activities within. While producing multiple representations of content may be an expensive proposition, standards such as the Sharable Content Object Reference Model (SCORM), a collection of standards and specifications for distributed learning applications, would allow the reuse of open source learning content objects to aid in reducing cost. Extensive SCORM-compatible content objects (commercial and open source) are available. In addition, research with artificially-intelligent agents is showing promise in developing content autonomously using data mining techniques via the internet (Gordon, 2010). These techniques can be used to develop narratives to support context-dependent knowledge acquisition and case-based learning. For example, data mining techniques could be used to search the online blogs of experts and extract relevant story lines about their experiences as military commanders and construct a narrative for leadership training.

Design that leverages CFT principles allows instructional content to support learners of varying preferences and mental models. Next, we will explore a theory that supports the building and revision of those mental models to support advances in learning.

Cognitive Transformation Theory in CBTS Design for Accelerated Learning and Retention

The traditional approaches to learning include: 1) defining learning objectives by comparing the student's knowledge and a standard needed for proficiency; 2) providing opportunities for practice; and 3) providing mechanisms for feedback (Klein and Baxter, 2006). This methodology is the foundation for many of the existing CBTSs (e.g., ANDES Tutor - Schulze, Shelby, Treacy, Wintersgill, VanLehn, & Gertner, 2000; PUMP Algebra Tutor - Koedinger, Anderson, Hadley, & Mark, 1997). Cognitive Transformation Theory (CTT) asserts that advanced problem solving on the part of students requires the recognition of flaws in their existing mental models. CTT links learning objectives to the student's current mental models and promotes processes for shedding flawed mental models for less flawed models through reflection and discovery. CFT and CTT make many of the same assertions. CFT and CTT each try to achieve growth but in different ways. For CFT, the focus is on flexibility and for CTT it is producing a better mental model.

Students may be unwilling to discard a mental model that they are comfortable with in lieu of a new model. A significant challenge exists for CBTSs to be able to help the student evolve their mental model through appropriate practice opportunities and feedback to support the student in discarding/adapting their existing flawed model to reach higher levels of understanding (Klein and Baxter, 2006). Understanding the student's states, managing their cognitive load and tailoring their experience are vital to selecting optimal strategies for learning.

It is also important to understand and define desired accelerated learning and retention outcomes to focus tutor design. The next section reviews CBTS approaches to tailored instruction, optimizing challenge and flow and balancing learning and retention strategies. All of these design approaches have potential to influence accelerated learning outcomes.

The Influence of Desired Accelerated Learning Outcomes on Tutor Design

In this section, design considerations for CBTSs in regards to accelerated learning outcomes are discussed including enhanced proficiency, performance and retention. Hoffman, Feltovich, Fiore, Klein, and Andrews (2009) state that proficiency, as a degree of competence, is a critical prerequisite to performance in complex work contexts. The terms novice, journeyman and expert are often used to describe the proficiency levels of students. It is critical that the tutor (human or computer-based) understand the student's level of proficiency in the domain being trained so appropriate decisions can be made about the presentation of content and instructional flow (Csikszentmihalyi, 1990). Hoffman and Feltovich (2010) posed the challenges of "rapidizing" training, accelerating proficiency and improving retention. To enhance efficiency, proficiency and retention, we considered the following approaches for the design of CBTSs: tailoring instruction to individuals of differing proficiency and motivation levels; optimizing the flow of instruction based on changes to the student's state; and balanced learning-retention strategies.

Campbell (1990) noted that individual differences in performance are a function of declarative knowledge, procedural knowledge, skill and motivation. The premise behind adaptive tutoring is to maintain the student in a "zone of proximal development" (Vygotsky, 1978) or a state of "ready to learn" where the flow and challenge level of instruction is appropriate to the student (Csikszentmihalyi, 1990; Murray, & Arroyo, 2003). By selecting instructional strategies that are marginally above the student's competency level, we can maintain their engagement level and their motivation to learn more challenging concepts. This has the potential to accelerate learning by minimizing the amount of time spent in a "low or no" learning state (e.g., boredom resulting from concepts perceived to be little or no challenge and confusion or frustration resulting from content that is at a significantly higher challenge level than their current capabilities).

Accelerating the acquisition of declarative and procedural knowledge could affect skill acquisition, motivation and retention in both positive and negative ways. On the positive side, more efficient acquisition of knowledge would allow for more time focused on skill development (sometimes called enrichment). Maintaining a "high" learning state minimizes boredom, confusion and frustration which would likely result in higher motivation/ commitment. On the negative side, rapid acceleration of learning could reduce opportunities for practice in increasingly difficult scenarios and thereby reduce opportunities to build expertise and retain knowledge/skills (Hoffman et al., 2009). It could also lead to burnout so the tutor must be sensitive to when and how quickly to accelerate learning.

Furthermore, the motivational aspects of tutoring should not be ignored. "When people have the right attitudes and commitment, learning automatically follows" (Argyris, 1991). Cordova and Lepper (1996) found that students exposed to motivationally-embellished educational software (Lepper, Woolverton, Mumme, & Gurtneret, 1993) had higher levels of intrinsic motivation. As a result, they became more deeply engaged by the interaction, and learned more in a fixed period of time.

Now that we have reviewed cognitive theories and their general influence on learning outcomes in tutor design, we will move forward in examining some fundamental approaches to accelerating learning through tailored interactions with CBTSs. These fundamental approaches may support more effective and/or efficient learning. In examining these approaches we must keep in mind that efficiency may be traded off for higher value learning (effectiveness). So the fundamental approaches to tailored instruction are meant to capture previous research and set the stage for our five accelerated learning design objectives.

Approaches to Accelerating Learning through Tailored Instruction in CBTSs

The need for tailored instruction fusing CBTSs is well documented (Woolf, 2010; Loll, Pinkwart, Scheuer, & McLaren 2009). A fundamental premise of CBTSs is that information about the student can be used to modify the presentation of information so that learning progresses efficiently (Johnson & Taatgen, 2005). Individualized guidance, assessment and feedback require an adequate model of the student's knowledge and skill, proficiency, progress, errors and misconceptions (Foster & Fletcher, 2003). These modeled student characteristics will be the primary determining factor for the specific tailoring approach executed in the learning experience.

The influence of motivation and affect on learning is also well-known (Picard, 2006; Heylen, Nijholt, Akker, & Vissers, 2003; Linnenbrink & Pintrich, 2002), but student models are still insufficiently robust to support tailored instruction that account for the student's motivational and affective states. Student models in CBTSs are largely built from dynamic sources (data that change during instruction) and static sources (historical data) (Neji & Ben Ammar, 2007; D'Mello, Craig, Sullins, &

Graesser, 2006; Picard et al., 2004; Murray & Arroyo, 2003). Dynamic data include physiological data (e.g., heart rate) and behavioral data (e.g., gesture) gathered from sensing technologies in near-real-time on a periodic basis (e.g., 20 measurements per second) and in-situ self-report data (e.g., reflections, preferences, feelings). Static data is only static in that it includes data that is unlikely to change during a single instructional session. Examples of static data include demographics, historical self-report data (e.g., preferences, goal-orientation, etc.), past performance, domain competencies and personality data that only change infrequently or not at all. Static data are normally stored in a learning management system (LMS) or other database format and are updated upon the completion of a lesson. Together dynamic and static data are used to classify student states (e.g., cognitive, affective). Combining sensing techniques (physiological and behavioral) might increase the accuracy of classification, but care should be taken to select techniques that are unobtrusive to minimize disruption to the learning process. It is important that sensing techniques are minimally distracting, do not detract from learning, and do not promote discomfort or frustration other than "desirable difficulties" needed to set learning.

The examples that follow illustrate the varying degree of tailoring implemented through student modeling in CBTSs. As noted above, tailoring is one strategy to enhance the efficiency of tutors and thereby accelerate learning, but it could also be used to make decisions about the challenge level of scenarios and thereby improve retention. One such example is the Parent and Child Tutor, a CBTS that provides personalized coaching strategies for parents who in turn tutor their children (Lahart, Kelly, & Tangney, 2007a). The tutor facilitates parents' learning by providing recommendations to promote positive emotional states in their children through the use of a set of 52 domain-independent tutoring rules based on four emotions (fear, anger, sadness and joy) observed in the children being tutored (Lahart, Kelly, & Tangney, 2007b). While this approach is adaptive, it is very prescriptive and does not account for the complexity of other variables (e.g., engagement, motivation) that can influence learning.

In another approach, Beal and Qu (2007) used student interaction data (e.g., mouse movement, control selection rates, hint requests) to model engagement, transient shifts in attention, cognitive effort and emotions associated with learning during CBTS sessions. The model, which included a Dynamic Bayesian Network, predicted student performance on a post-test of math achievement in instances where the pre-test performance did not. Being able to predict future performance (e.g., at, below or above expectations) allows the CBTS to formulate appropriate instructional strategies. For instance, if the network predicted low performance, it could assess contributing factors for low performance based on the context, cognitive state (e.g., engagement level) and the affective state (e.g., motivational level) and then adapt the content to provide a review of key concepts (e.g., flow change or remediation strategy), provide feedback to positively affect motivation (e.g., supportive encouragement) or guide an opportunity for reflection (ala CTT).

The ability of the CBTS to recognize engagement and predict performance will enhance the ability of tutors to keep students in high learning states and perhaps make accelerated learning possible. D'Mello, Craig , Sullins and Graesser (2006) and D'Mello and Graesser (2007) used the student's conversation patterns to classify one of three affective states (confusion, 'eureka,' frustration). Based on the student's classified affective state and the instructional context, the tutor provided appropriate feedback, pumps, hints and assertions to influence student's motivation and engagement.

Finally, we include physiological sensing techniques that aid in modeling cognitive and affective states that allow selection of appropriate instructional strategies and thereby influence learning and retention. The effectiveness of this physiological modeling approach is limited and is prone to error due to noisy data produced by the sensors (Ward & Marsden, 2003). For example, Blanchard, Chalfoun and Frasson (2007) developed a predictive model incorporating multiple physiological sensors for determining cognitive workload and emotional response to stimuli. Electroencephalography, galvanic-skin response, skin temperature, respiration rate, heart rate and facial feature tracking were used to provide a multimodal modeling approach to observe correlations among physiological markers as a response to environmental stimulus. Blanchard et al. (2007) found predictive inaccuracies in the resulting models due to the oversimplification of physiological data. Methodologies are needed that can support the real-time (or near-real-time) assessment of physiological data and its indication of transient affective and cognitive states.

We have reviewed the potential influence of tailoring instruction, various methods of sensing, assessing and tailoring instruction. Now, it is time to examine recent approaches to optimizing challenge level and flow and their influence on learning outcomes.

Approaches to Optimizing Challenge and Flow in CBTS

Significant emphasis should be placed on balancing the student's proficiency with the challenge level of instruction to maintain motivation and to avoid long-term states of confusion, frustration, overstimulation and boredom (Csikszentmihalyi, 1990; Murray & Arroyo, 2003). Sessink, Beeftink, Tramper and Hartog (2007) asserted that "most traditional learning material targets the 'average student', and is suboptimal for students who lack certain prior knowledge, or students who have already attained some of the course objectives." To support learning, comprehension and remembering, Bjork (1994) advocates manipulations within the instruction that introduce "desirable difficulties" for the student. Examples include, but are not limited to: varying the conditions of learning; providing "contextual interference" during learning; distributing or spacing study or practice sessions; and using tests as learning events.

Introducing difficulties during instruction has the added benefit of focusing the student's attention. Yun, Shastri, Pavlidis and Deng (2009) demonstrated the interpretation of a thermal camera, StressCam, to estimate student stress levels. They altered the difficulty levels of game play for students based on singular input from StressCam, which monitored heat dissipation in the forehead. Since stress levels are related to increased blood flow and higher blood flow equates to more heat, StressCam passively and continuously senses and interprets thermal images as stress states. Using this type of closed-loop system allowed for adaptation of the challenge level of the game. Challenge level could be lowered when stress was too high to support effective learning and increased to avoid boredom, thereby maintaining the student in a zone of proximal development.

Not only is there a need for optimizing challenge and flow, there is also a need for a balanced approach to learning and retention. Accelerating learning (short term) may be at odds with retention objectives (longer term) as discussed below.

Approaches to Balanced Learning-Retention Strategies in CBTS

While it is important to develop instructional strategies to accelerate learning, it is equally important to consider how the design of CBTSs will facilitate retention. "Retention of knowledge and skill is better when material at the time of acquisition is processed deeply, embellished, and connected to, and integrated with other knowledge" (Hoffman & Feltovich, 2010). To facilitate retention, a CBTS will have to take into account a long-term view of the student. Most tutoring systems today are focused mainly on progress in a single domain of instruction and fail to address long-term student modeling. To achieve this, tutors will need to be integrated with an LMS to support even a career-long learning capability and address retention as well as the acquisition of knowledge and skills.

Since retention of knowledge and skills is highly dependent on the opportunity to practice, CBTS capabilities should include a service-oriented architecture. The service-oriented architecture approach would allow for access to tutoring any place and anytime. The tutoring capability should also include a program of spaced repetition (also known as spaced rehearsal). This technique facilitates retention by gradually increasing intervals of time between each subsequent review of previously learned content (Baddeley, 1990; Spitzer, 1939). Finally, the authors advocate incorporation of Bjork's (1994) "desirable difficulties" into the

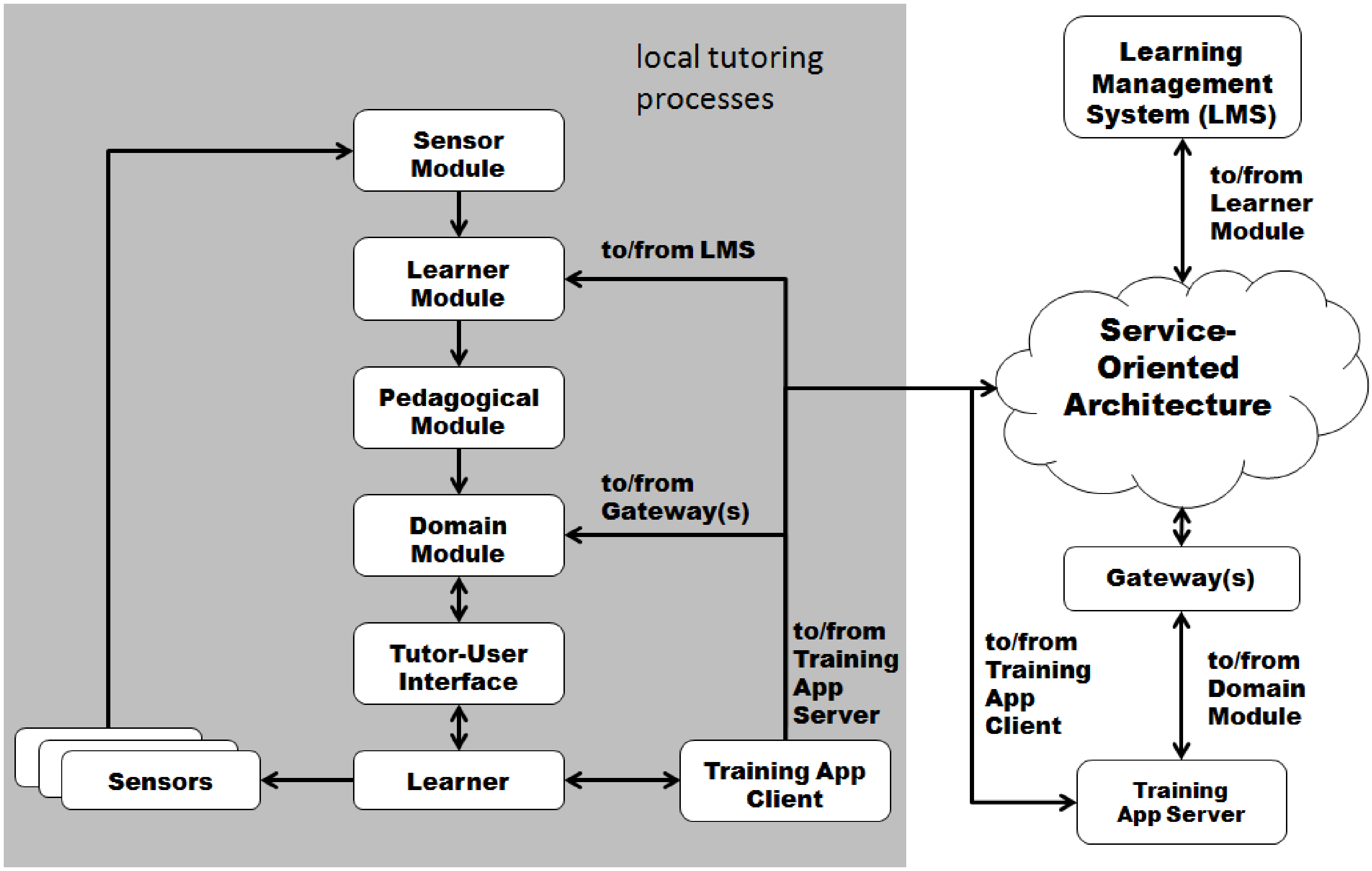

***Figure 2*. Generalized Intelligent Framework for Tutoring (GIFT)**

domain knowledge of any CBTS. This incorporates the inclusion of learning experiences that makes initial learning difficult but makes recall and application of facts easier at later instances.

Having reviewed current approaches to tailoring instruction, optimizing challenge and flow, and balancing learning and retention strategies, we now focus on tying accelerated learning principles and learning theories to our proposed CBTS design objectives. Along the way, we will also discuss how our evolving design of GIFT supports these CBTS design objectives.

Accelerated Learning Principles and Their Influence On Tutoring Design

The connection between learning theories (e.g., CLT, CFT, CTT) and the integration of accelerated learning principles has been noted above. Now, we discuss the connection between accelerated learning principles and effective scenario-based tutoring design as described in the GIFT. The benefits of scenario-based training include the opportunity to practice tasks in relevant environments, to apply knowledge and to be exposed to scenarios of varying levels of challenge and complexity. According to Hoffman and Feltovich (2010) effective scenario-based training includes scenarios that are challenging and novel to the student as described by the CFT and the CTT. The challenge level and novelty of any scenario is highly dependent on the competency level of the student and further highlights the need for student modeling and tailored strategies in tutor design.

In Figure 2, GIFT elements and interactions are highlighted so we might compare and contrast the core CBTS model presented in Figure 1 as a prelude to discussing how GIFT supports the five design objectives put forth in this article. The most significant difference between GIFT and CBTS is the isolation of domain knowledge which provides the opportunity to maintain other GIFT elements (sensor module, student module and pedagogical module) as domain independent.

In reviewing the literature, some common principles associated with accelerated learning were identified. Common themes included tailoring based on student needs and providing practical, case-based scenarios. Moon, Birchall, Williams and Vrasidas (2005) defined accelerated learning design themes for an e-learning system that is highly analogous to the CBTS context reviewed in this article. Below, we discuss five accelerated learning design objectives for CBTS capabilities and how GIFT has been designed to support these objectives.

Design Objective #1: Support Efficient, Tailored Instruction through Comprehensive Student Modeling

Methodologies for tailoring instruction are well documented (Woolf, 2010; Karagiannidis, Sampson, & Cardinali, 2001; Picard et al., 2004) and center around unique student modeling. According to Wenger (1987), all student models must perform three tasks: (1) the model must gather data from and about the learner; (2) the data must be used to build an interpretation of the learner's state; and (3) the interpretation is used for performing a diagnosis of pedagogical strategies to carry out the presentation of subsequent information.

To this end, many techniques and theories have been applied to modeling student states (e.g., competence, engagement, affect) with varying degrees of success. Examples of tutors with explicit student models include the LISP Tutor (Anderson, 1990), the PUMP Algebra Tutor (Koedinger, 1997), Wayang Outpost (Arroyo, 2004) and AutoTutor (Jackson, Mathews, Lin, Olney, & Graesser, 2003). GIFT, being developed at the U.S. Army Research Laboratory, also contains an explicit student model. GIFT is an authoring system for CBTS, a tutoring technology assessment tool and a communications architecture that is being designed to integrate tutor logic (e.g., trainee models, domain knowledge, pedagogical models), learning management systems and learning resources. The student model in GIFT provides a multi-dimensional view of the student's states and traits. Short- and long-term views of the student's cognitive and affective states, knowledge and proficiency are included in the student model with the more static views of biographical data and preferences stored in an LMS. The data in the student model is used to inform various predictive techniques (e.g., clustering algorithms, Bayesian networks or Markov Decision Processes) to ascertain the student's state or assess optimal instructional strategies.

Substantial research remains to optimize the structure of the student model to include states and traits that might be generalized across learning contexts and student populations. The student model also contains domain-specific information extracted from the LMS about the student's training performance in various training domains (e.g., bi-lateral negotiation, casualty care). This information may also be used to inform predictive models or techniques.

The student model in GIFT has been designed to be sufficiently robust to allow the tutor to tailor scenarios to be relevant to the student's own experiences. Student modeling research includes investigation into individual differences that influence accelerated learning and retention. For tutoring systems, states/traits of interest to possibly model include, but are not limited to: engagement, motivation, and affect (personality, mood and emotions).

Unobtrusive behavioral and physiological sensing technologies (D'Mello & Graesser, 2007; Sottilare & Proctor, 2012) are showing great promise in assessing student states (e.g., frustration) that may not always manifest themselves in obvious ways. Multiple sensing methodologies that are integrated with contextual data (e.g., scenario) are showing higher accuracy in classifying cognitive and affective states (Wingrave, Hoffman, LaViola, & Sottilare, 2011), and will improve the appropriateness of instructional strategy selected by the tutor.

Design Objective #2: Support Active, Case-Based Learning

A CBTS should enable training in practical, not theoretical, contexts in order to tie knowledge acquisition to a relevant real-world scenario or case study. The scenarios/cases should be sufficiently complex to challenge students to construct new or adapt old knowledge representations and they should motivate or require the student to actively interact with the scenario. Case studies allow the student to generalize lessons-learned in the case to other contexts and solve problems relevant to the student. This would allow the student to construct knowledge representations based on relevant experiences that may transfer more easily later to an operational context. It might also allow new experiences to motivate the student to shed old knowledge models in favor of newer, more complex models per the CTT.

Design Objective #3: Divide Training Content into Manageable Chunks

Moon et al. (2005) recommend instructional designers divide courses into small "discrete" sections which can stand alone or be used as part of more complex activities when joined with other learning content objects. Whereas novices may be capable of only dealing with a few small chunks of knowledge, more proficient learners are capable of integrating a greater number of chunks (and larger chunks) to construct more complex knowledge representations.

As noted earlier, sharable content objects are the premise behind the SCORM standard. Small "chunks" of instruction offer maximum flexibility in creating new instructional objects from existing objects, and provide flexibility for the student to navigate the instructional material and construct their own unique knowledge representations as advocated by CFT.

Design Objective #4: Support Reflection and Social Learning

Reflection is defined by Boud, Keogh and Walker (1985) as "intellectual and affective activities in which individuals engage to explore their experiences in order to lead to a new understanding and appreciation." Donald Schön (1983) discussed reflective thinking long before Boud et al. (1985) and Epstein and Hundert (2002) highlighted the relationship between competence and reflection in their definition of professional competence: "professional competence is the habitual and judicious use of communication, knowledge, technical skills, clinical reasoning, emotions, values, and reflection in daily practice for the benefit of the individual and community being served." Reflection during the learning process is valuable in building new understanding of experiences (Boud et al., 1985). Activities typically associated with reflection include personal journals and social learning through small group discussion (Harris, Pereira, & Davidson, 2000). In addition to personal journals, Laurillard, Stratfold, Luckin, Plowman, and Taylor (2000) recommend that the tutor support and guide student reflection. Gouli, Gogoulou, Papanikolaou and Grigoriadou (2006) developed an adaptive framework to support reflection, guiding and tutoring.

In a study of expert human tutors, Lepper and Woolverton (2002) argued that the most effective tutors are themselves reflective. Lepper and Wolverton (2002) included reflective functions for "articulation," "explanation" and "generalization." These are also desirable characteristics for a CBTS. For "articulation," tutors ask students to reflect aloud right after the successful completion of a problem, to help the student understand the concepts and operations used in the problem and to ascertain any misconceptions about the problem. For "explanation," the student is asked to explain their answers and the procedures used in problem solving. Finally, for "generalization," the student is asked how the problem they just solved might relate to other problem spaces to help in transferring knowledge and skills to other domains.

Supporting social learning is also an objective recommended in CBTS design. Social learning is learning that is "influenced by social interactions, interpersonal relations, and communication with others" (Alexander & Murphy, 1998). Social interaction can positively affect the students' sense of belonging and self-efficacy (Richardson & Swan, 2003). Just as an accelerated learning-friendly tutor provides contextually relevant experiences or case studies for the student, it must also provide contextually-relevant meaningful feedback and interaction. Contextual cues of communication are important in creating a feeling of social presence during training (Richardson & Swan, 2003). Care should be taken in the tutor design to insure that interaction between the student and the content, the student and the tutor, and the student and other students (Vrasidas & Glass, 2002) is enabled to supports reflective and social learning activities in relevant contexts.

Design Objective #5: Test for Understanding

Opportunities to test for understanding during the training experience are also opportunities to learn. The National Research Council (2005) identified an “assessment-centered” approach to learning, which emphasizes the need to provide frequent opportunities to make the student’s thinking and learning apparent as a guide for both the tutor and the student during instruction. While testing alone is not a guarantee of future learning success, testing early and often means that the tutor will be able to identify that student has misconceptions about the instructional content early and make adjustments to instructional strategies (e.g., content, flow and challenge level) earlier and avoid wasted time spent later in the instruction on vaguely understood principles or concepts. This design objective is congruent with CTT, which asserts that advanced problem solving requires students to recognize flaws in their existing mental models. Frequent testing promotes the opportunity to assess and shed flawed mental models for less flawed models through reflection and discovery. The best tutors understand common misconceptions in any given training domain and distinguish between significant errors that hamper learning and those that are less consequential (Lepper & Woolverton, 2002; Hoffman, 1998).

Recommendations for Future Research

We present three recommendations for additional research to more deeply integrate accelerated learning principles into CBTS design. The first recommendation revolves around the importance/influence of individual differences within instructional design. There is much in the literature about the need to address individual differences in instructional design. What are lacking are studies to evaluate and validate the individual differences that are substantively important, and the effect size of those individual differences has on learning and retention. Research is needed to examine the portability of individual student modeling and tailored instruction across populations and training domains. Significant work has been done regarding individual and team performance (Salas, Rosen, Held, & Weissmuller, 2009). Additional research is needed to evaluate the influence of learning styles, personality preferences, individual values, group/organizational values, contextual affect (e.g., frustrated about a reflective exercise), age, gender, cognitive ability level, education level and culture on instructional decisions and ultimately, their influence on accelerating learning and facilitating retention.

Our second recommendation is in the area of instructional strategy selection. Assuming a tailored student model is developed that includes significant influencers/predictors of learning outcomes, the strategies for selecting appropriate instructional changes (e.g., challenge level, flow, questioning, hinting) will need to be optimized for accelerated learning and retention outcomes.

Our third recommendation for future research is to apply the INSPIRE Model (Intelligent, Nurturant, Socratic, Progressive, Indirect, Reflective and Encouraging) of tutoring success (Lepper, Drake, & O'Donnell-Johnson, 1997) to CBTS design and assess its effect size. Based on a long-term study of successful human tutors, INSPIRE integrates several best practices discussed within this article, and may be the most promising model to translate successful human tutoring practice to CBTS.

Our final recommendation is to research and develop a capability to author and evaluate accelerated learning and retention tutoring concepts easily for individual, team, social learning and mobile learning contexts. Today, most CBTSs are one-of-a-kind, handcrafted programs whose components were not designed to be modular or reusable. Integrating existing standards and developing new standards will enhance the capability of researchers to evaluate new accelerated learning concepts. The GIFT concept is being developed to support summative evaluations of CBTS.

Conclusions

We have observed significant correlations between accelerated learning and retention principles and effective CBTS design. Three cognitive theories were reviewed along with their implications for effective tutor design and positive accelerated learning outcomes. To achieve enhanced efficiency, proficiency and retention outcomes, the authors also proposed three design approaches focused on 1) tailoring instruction based on individual differences (e.g., proficiency and motivation); 2) optimizing the flow of instruction based on changes in the student's state; and 3) balancing learning and retention strategies within CBTS to maintain high states of learning and sufficient difficulties for students to build their own unique knowledge representations.

Finally, based on the literature, the authors proposed a set of five accelerated learning and retention design objectives for CBTS.

AUTHOR NOTES

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