ADAPTIVE INSTRUCTIONAL METHODS TO ACCELERATE LEARNING AND ENHANCE LEARNING CAPACITY

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ABSTRACT
This paper examines adaptive instructional methods to accelerate learning and improve learning capacity. Adaptive instruction provides tailored, computer-based learning experiences based on the needs and preferences of the learner. Often the goal is to optimize learning, performance, retention, and transfer of skills from instructional environments to work/operational environments. In this case, we shall examine methods to accelerate learning (improve instructional efficiency) and enhance learning capacity (improve instructional effectiveness) during adaptive instruction using Intelligent Tutoring Systems (ITSs). Specifically, we will examine best practices incorporated or emerging in ITSs authored by the Generalized Intelligent Framework for Tutoring (GIFT; Sottilare, Brawner, Goldberg, Holden 2012; Sottilare, Brawner, Sinatra, and Johnston, 2017) GIFT is a prototype, free, open-source architecture for authoring, managing, and evaluating ITSs and adaptive instruction.

Keywords: adaptive instruction, accelerated learning, instructional efficiency, instructional effectiveness, Intelligent Tutoring Systems (ITSs), Generalized Intelligent Framework for Tutoring (GIFT)

1. INTRODUCTION

Intelligent Tutoring Systems (ITSs) provide effective one-to-one instruction predominantly in well-defined domains like mathematics, physics, and software programming. ITSs have been shown to be as effective as expert human tutors (VanLehn, 2011) and therefore should be an instructional tool of choice for self-paced, computer-guided learning. The Generalized Intelligent Framework for Tutoring (GIFT; Sottilare, Brawner, Goldberg & Holden, 2012; Sottilare, Brawner, Sinatra & Johnston, 2017) is a prototype, open-source architecture for authoring, managing, and evaluating Intelligent Tutoring Systems (ITSs) and adaptive instruction where computer-based intelligent agents guide learners based on their learning needs, preferences, and progress toward learning objectives, which are called concepts in GIFT.
Thorndike (1906) inferred the importance of adaptive instruction in training and education long before ITSs ever existed: “The principal consequence of individual differences is that every general law of teaching has to be applied with consideration of the particular person … [which] will vary with individual capacities, interests, and previous experience.” Adaptive instructional systems use learner attributes to tailor instruction for each individual learner or team, and specifically to drive instructional decisions (e.g., selection of future content and experiences or feedback type and frequency). This paper examines how adaptive instruction might be used as a tool to: 1) improve instructional efficiency by reducing the time needed to learn a fixed set of concepts (accelerating learning) and 2) improve instructional effectiveness by increasing the amount of material that can be learned in a fixed amount of time or improving learning capacity.

2. ENHANCING INSTRUCTIONAL EFFICIENCY

The goal of enhancing instructional efficiency is to reduce the time for learners to reach a desired level of knowledge and/or skill. Training efficiency is a relevant measure when the goal of the training is to insure that all learners attain a standard level of proficiency/knowledge. For example, organizations often have recurring training requirements to insure that individuals in the organization maintain critical knowledge and skills. In such situations, adaptive training has the potential to reduce the time needed to train for some percentage of the population (Figure 1).

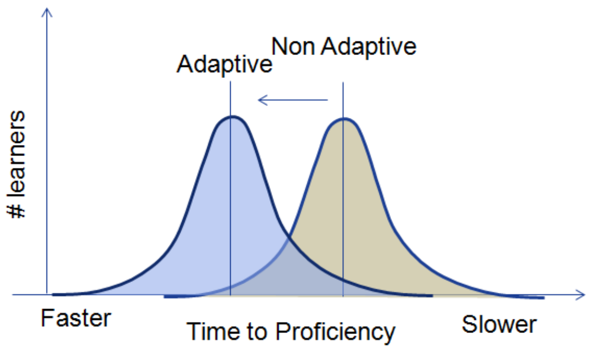

Figure 1: Enhancing Learning Efficiency

A key adaptation provided by ITSs is tailoring of content based on each learner’s prior knowledge of the task domain. This reduces the amount of content shown to the learner, but varies with the learner’s competence with high competency learners able to skip the most content. While this saves time during instruction, it should be noted that some review of material is required on a periodic basis to maintain proficiency, and skipping content does not accelerate learning. It only saves time spent in training or education that might be used to cover new material.

To improve training efficiency, Goodwin, Kim, and Niehaus (2017) recommend prioritizing design decisions based on a cost-savings comparison. Specifically, the cost of implementing adaptive features should be compared to the savings resulting from improved efficiency. Only features that save more than they cost should be implemented.

These recommendations and accelerated learning as a concept fly in the face of long term, deep learning goals. To overcome this, the tutor must have a highly accurate model of the learner by which to make instructional decisions. Many ITSs today only adapt based on learner performance. This has been a very clear choice. Selecting to adapt on other learner states, traits or preferences imparts some risk in the tutoring process.

3. ENHANCING INSTRUCTIONAL EFFECTIVENESS

The goal of enhancing instructional effectiveness is to increase the learner's capacity to acquire knowledge and/or skill in a fixed time. The assumptions for measuring effectiveness are that the amount of material to be learned is variable and the learning time is fixed (Figure 2). Since what is learned is variable, learners may be below, at, or above expectation in terms of their mastery of the material at the conclusion of the training time. Adaptive instruction has the potential to be more effective because it can address specific learner problems and employ a variety of methods known to be effective for each individual.

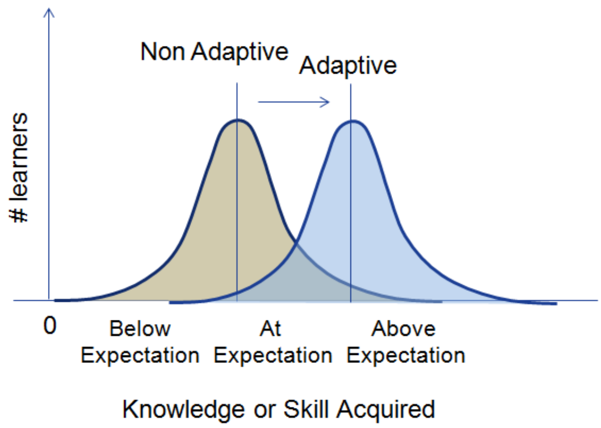

Figure 2: Enhancing Learning Effectiveness or Capacity

To support enhanced learning effectiveness or learning capacity, Goodwin, Kim, and Niehaus (2017), recommend methods to more accurate diagnose learner errors, tailored remediation, and tailored training methods. Each is important, but might include additional sub-goals. Diagnosis of the learner might include accurate classification of all critical learner states. In addition to learner errors, this might include assessment of learner performance trends (short and long term), diagnosis of learner misconceptions indicated by errors. Tailored remediation and training methods might be expanded to include tailored interaction. Not only feedback could be adapted to specific learner performance, but other states, traits, and preferences. Adaptation could also include preference tailoring in which the environment is adapted to the specific learner's cultural background to provide a familiar mental model for learning. This could enhance learner engagement and result in less down time during instruction. Another adaptation to improve effectiveness could include tailoring based on learner interests.

4. DISCUSSION

As the foregoing indicates, training efficiency and training effectiveness are goals that are sometimes at odds with one another. When seeking to minimize time to train, it is sometimes necessary to sacrifice deep learning or overtraining. When seeking to maximize long-term retention or knowledge and proficiency, it will be difficult to simultaneously reduce training time. We discuss these tradeoffs in the design of adaptive instruction in the context of 1) training vs. education, and 2) individual vs. team learning.

4.1. Adaptive Instruction in Training vs. Education

According to Fletcher (2017), training and education serve different purposes. These differences moderate, influence, or limit the effect of adaptive instructional methods and should be considered in the process of instructional design. We will focus on two factors and how these relate to learning efficiency and effectiveness.

The first factor is the difference in the objectives for training and education. Training objectives are focused on learning to do a specific task or set of tasks in the operational or work environment. Educational objectives are much broader and focused on preparing to perform in yet unknown environments. If you think of training as a pebble and education as a boulder based on their relative complexity, it is much easier to move a pebble. The sheer differences between the scope of training and education are likely to result in different levels of effect when applying adaptive instructional methods. It is much more likely that adaptive instruction will have an impact on learning efficiency in training given there are smaller, less complex domains/environments encountered during training.

A second consideration in the differences between training and education is the difference in horizon. Training tends to focus on near-term goals while education has a much longer horizon. This temporal difference means the emphasis for training is on "return on investment" while education is more about "cost effectiveness" (Fletcher 2017). Return on investment (ROI) is the ratio of net gain (or benefit) to cost. If you have to invest an hour to acquire a unit of knowledge/skill, it is much more efficient than taking two hours to acquire the same knowledge/skill. Cost effectiveness is about producing optimum results for a fixed expenditure. So training may be more conducive

to adaptive instructional methods that emphasize efficiency (learning as fast as possible) while education may be more compatible with methods that emphasize effectiveness (learning as much as possible).
Finally, ROI or cost effectiveness of adaptive instruction should consider not only the cost to the learner (e.g., time invested in instruction), but also the cost of creating the content and the adaptive tutor (Fletcher and Sottilare, 2014).

4.2. Adaptive Instruction for Individuals vs. Teams

Another area where differences should be considered for the design and application of adaptive instruction is individual and team (also known as collective) instruction. While ITSs adapt instruction based on individual differences (states, traits, and preferences), an ITS that adapted only on the individual differences of the members of the team would likely be less effective (and efficient) than an ITS that also modeled the collective needs of the team. Teams are "two or more people whose tasks are in some way interdependent (i.e. individual efforts are dependent upon the efforts of other members) and who have shared, common goals" (Salas 2015, p.3.; Dyer 1984; Kozlowski & Bell 2003; Salas, Dickenson, Converse, & Tannenbaum 1992).
Considerations for the adaptive instruction of teams should examine the interaction of team members which may be subdivided into teamwork and taskwork. Teamwork is "coordination, cooperation, and communication among individuals to achieve a shared goal" (Salas 2015, p.5.). "Teamwork consists of the interdependent interactions among team members as they work towards completing their objectives" (Salas 2015, p.5.). Taskwork consists of "working on a specific duty of one's job [within a team]" (Salas 2015, p.5.). Team taskwork refers "to those relevant behaviors that directly lead to the successful accomplishment of collective goals" (Salas 2015, p.5.). Teamwork may be considered largely domain-independent while taskwork is specific to a domain.
The point being made here is that teams, their behaviors, and their interactions are much more difficult to assess with respect to learning objectives and teamwork. Therefore adaptive instruction of teams is more complex than adaptive instruction individuals. This makes accelerating learning and improving learning capacity much more difficult than for individuals, and impacts the return on investment and cost effectiveness of adaptive instructional methods.
Prioritizing efficiency vs effectiveness in team training may be driven more by the criticality of the team's function than anything else. For example training for a medical team performing a complex surgery will likely prioritize training effectiveness because there is such a low tolerance for error. On the other hand training for a team of food preparers in a fast-food restaurant might prioritize training efficiency since the individuals will be working together on a daily basis and the cost of error is minimal.

5. APPLICATION OF ADAPTIVE INSTRUCTIONAL METHODS IN GIFT

Next, we examine authoring capabilities in GIFT for adapting instruction to accelerate learning and enhance learning effectiveness. GIFT allows the author to adapt instruction based on several factors in two primary areas: learner attributes and content attributes.

5.1. Adapting Instruction Using Learner Attributes

Data sources (e.g., people) emit raw data that is captured by sensors and then processed by a classifier to yield a learner state unless the state is self-reported. Each learner state can be assessed with data from a sensor, a training application or a survey depending on the validated methods available. Each state can be assessed as either a two (high and low) state or a three state (high, moderate, and low) attribute.
A five step process allows GIFT users to create new learner state interpreters as follows:

- Step 1: What learner state interpreter would you like to create? This step includes a dropdown menu that lists the six previously mentioned state interpreters plus off-task behaviors, skill, and understanding.
- Step 2: What data sources will be used to evaluate and predict the learner's state? This step includes a dropdown menu that lists eleven sensors that have been integrated with GIFT and are able to accept and interpret data from each of those sensors. These sensors include: Affectiva Q sensor for electrodermal activity, Microsoft Kinect for motion capture and facial marker mapping, Emotive Epoc wireless headset for brainwave detection, and Zephyr BioHarness for breathing and heart rate detection.
- Step 3: Which translator should be used to manage incoming data? GIFT provides a default translator, but users may build their own to filter or interpret incoming data.
- Step 4: Which classifier can consume the incoming translated data in order to calculate both short and long term learner states? Choices will be limited to a classifier based on the learner state selected in Step 1.
- Step 5: Which predictor can consume the incoming translated data in order to predict future learner states?
- Choices will be limited to a classifier based on the learner state selected in Step 1.

Once the learner state interpreter is configured, it should be validated for accuracy of predictions. The importance of highly accurate state classifiers cannot be understated. Even small errors can multiply if the tutor assumes an incorrect state and begins remediation based on that false assumption. Currently, GIFT adapts instruction based on assessed learner states as follows:

- engagement
- arousal
- motivation
- prior knowledge
- anxiety
- engaged concentration

5.1.1. Engagement and Learning

Engagement is "the degree of attention, curiosity, interest, optimism, and passion that students show when they are learning or being taught, which extends to the level of motivation they have to learn and progress in their education" (Hidden curriculum, 2014, August 26). The value of engagement is predicated on the tenet that learning is enhanced when learners are curious, interested, and/or inspired by the topic, content or instructor. In contrast, learning tends to decrease when students are disengaged for whatever reason (e.g., boredom, disinterest, or lack of purpose or goal). Accurate modeling of the learner and their goals can go a long way toward adapting instruction in a way that results in more efficient learning (accelerated learning) or effective learning.

5.1.2. Arousal and Learning

Arousal is a "physiological and psychological state of being awoken or of sense organs stimulated to a point of perception" (Wikipedia, 2017). Yerkes-Dodson (1908) state that too much or too little arousal can negatively influence task performance, and Sharot & Phelps (2004) note the tight coupling between memory and arousal which affects learning capacity. By understanding the learner's arousal from boredom to interest, a tutor (human or computer-based) might change either the environment (e.g., challenge level of a problem or scenario) or otherwise interact with the learner to optimize their arousal and thereby their learning (Figure 3).

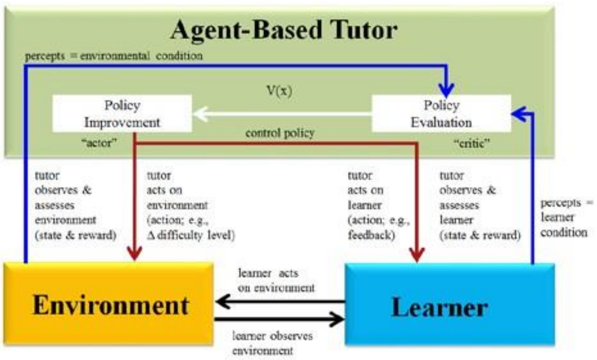

Figure 3: Optimizing the Arousal of the Learner

5.1.3. Motivation and Learning

Motivation can be defined as the purpose or reason driving the plans and actions of an individual or a team (Elliot & Covington, 2001), but it may be thought of simply as an alignment of actions with goals. The more closely aligned actions/activities are with individual or team goals, the more engaged the learner(s) will be in the activity, and the greater the opportunity for learning (knowledge and skill acquisition).

Goals are often driven by values which are shaped by many sources (e.g., family, religion, society, needs, and organizations), but may also be prioritized as in Maslow's (1971) hierarchy of needs. The tie between motivation and goals has a direct impact on learning. Motivation positively influences cognitive processes by increasing the learner's attention time on task, influencing their perseverance in the learning process, and sharpening their focus on achieving their goals (Pintrich & Schunk, 2002). By considering the goals, interests, and values of a learner, a GIFT-based ITS might select content and activities which tap into existing motivational drives and enhance learning.

5.1.4. Prior Knowledge and Learning

Prior knowledge includes the knowledge, skills, beliefs, and attitudes derived from previous experiences, and learners come to new instructional experiences with prior knowledge that influences their attention, interpretation, and organization of new data, information, and knowledge. The ability of the tutor to model and use prior knowledge to inform instructional decisions is directly related to learning efficiency and effectiveness. Instructional strategies that focus too heavily on prior knowledge can lead to boredom while focusing too lightly on prior knowledge may not provide enough of an anchor to tie in new knowledge resulting in learner anxiety. Prior knowledge may be used in GIFT-based tutors as a trigger to skip content that may have been learned previously. Errors and classified learner misconceptions trigger the tutor to review material that may not have been deeply learned.

Prior knowledge may be used differently to achieve training efficiency vs training effectiveness. Assessing the learner's prior knowledge can allow the adaptive training system to skip content which might improve efficiency. When focusing on effectiveness however, the system might give learners with more prior knowledge more advanced training to bring them to a higher level of proficiency.

5.1.5. Anxiety and Learning

Anxiety is "a feeling of worry, nervousness, or unease, typically about an imminent event or something with an uncertain outcome" (English Oxford Living Dictionaries, 2017). Since "learning" is about acquiring knowledge and/or skill through new experiences with uncertain outcomes, it is little wonder that anxiety and learning are generally incompatible. To confirm learning, instruction often includes some type of assessment of the knowledge or skill defined in the learning objectives. This assessment or test can also be a source of anxiety. Computer-based instructional environments can provide a setting for learner anxiety to grow due to lack of trust in the technology or due to the difficulty of the domain content or the use of its interface (O'neil, Spielberger & Hansen, 1969).

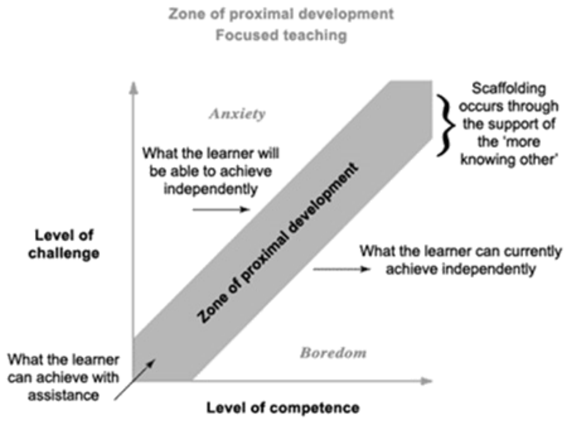

Figure 4: Aligning Content Difficulty with Learner Competence to Reduce Anxiety and Boredom

Per Vygotsky's zone of proximal development (VPD; 1978; Figure 4), an anxious learner who appears to be overwhelmed by the difficulty of the content being presented during instruction is compatible with two instructional strategies. The first strategy is to reduce the difficulty of the content presented to the learner so it is compatible with the learner's capabilities. The second strategy is to have the tutor provide scaffolding or support allow the learner to progress in learning the content at the current difficulty level. The effectiveness of instructional strategies or aids may be quantified by examining task performance with and without the aid at various levels of expertise (e.g., very low, low, moderate, high, very high). The effect of the aid may vary with the level of learner expertise. GIFT allows the author to select these strategies through selected triggering events or automatically through built in logic.

5.1.6. Engaged Concentration and Learning

Baker, D'Mello, Rodrigo, & Graesser (2010) define engaged concentration as a cognitive–affective state that may be of short duration, but more persistent than boredom. Engaged concentration is a state of engagement with a task where the learner is fully immersed in the experience and their "concentration is intense, their attention is focused, and their involvement is complete". In comparison to boredom, frustration, confusion, delight, and surprise, engaged concentration was common (average of 60% of learner time during instruction) and appeared often in computer-based learning environments.

According to Baker et al (2010), engagement concentration is of positive valence and neutral arousal. In addition to immersion, focus, and concentration on the system, Baker et al (2010) also noted additional behaviors associated with engaged concentration: leaning towards the computer, mouthing solutions, and pointing to parts of screen. Engaged concentration has been found to be positively correlated with learning (Craig, Graesser, Sullins, & Gholson, 2004; Graesser, D'Mello, Chipman, King, & McDaniel, 2007). A natural tutoring strategy for a learner in the state of engaged concentration might be to "do nothing" since the learner is already in an ideal state for learning.

5.2. Adapting Instruction Using Content Attributes

The pedagogical configuration in GIFT allows users to adapt instruction based on assessed learner states within the engine for managing adaptive pedagogy (eMAP) and content metadata attributes as follows:

- interactive multimedia instruction (IMI) level
- user control
- difficulty level
- content type
- example type

5.2.1. IMI and Adaptive Instruction

IMI (Galbreath, 1992) includes four levels to describe the interactivity of content where 1 is low interaction (e.g., reading material) and 4 is highly interactive (e.g., a fully immersive virtual simulation). Frear & Hirschbuhl (1999) indicate that the selection of the interactivity level of content has a significant effect on both achievement and problem solving skills. Lee and Boling (1999) advocate guidelines for screen design during IMI to both enhance motivation (expansive guidelines) and reduce poor practices which might negatively impact motivation (restrictive guidelines). Expansive guidelines include the use of fonts to capture the learner's attention to make it easier to navigate content, and the use of standard images to represent the learner's concepts and expectations (e.g., pause, rewind, and fast forward for video controls). Restrictive guidelines include adhering to cultural conventions when selecting images, and considering the learner's prior knowledge when selecting images. While the GIFT authoring tools do not specifically enforce these conventions, future versions of the authoring tools may include agent-based policies/rules or wizards to reinforce good IMI practices which are independent of learner attributes.

5.2.2. User Control and Adaptive Instruction

For our purposes, user control for adaptive instruction may be defined as being synonymous with adaptability in system design where the decisions and actions by the learner mold the look, feel, and function of the learning system. We adopted Oppermann & Rasher's (1997) provisions for user control for adaptive learning systems:

- offer the learner a means to initiate/halt adaptation of the system during every phase of learning
- allow the learner to accept, modify or reject every or any part of proposed adaptation
- enable the learner to specify adaptation parameters
- inform user about the proposed changes due to adaptation before actual changes take place

- giving the learner access and sole control over his/her behavior records and their evaluation (open learner model)

In GIFT, user control is defined at three levels (high, moderate, and low) where high user control would be modeled per Oppermann & Rasher's (1997) provisions. While GIFT does not yet provide a high level of learner control, triggers have been integrated to implement a moderated level of learner control (specifically, an open learner model). GIFT allows the author to select and link levels of user control to a variety of learner and content attributes with the goal of influencing learning and transfer. Hassan, Ali, & Hamdan (2015) evaluated several user control strategies for instruction with animation content, and found random user control strategies had a larger effect on achievement than other user control strategies (e.g., linear, program, free, and no user control). Mayer & Chandler (2001) discovered that learners who were allowed to exercise control over the pace of content presentation performed better in terms of their transfer of skills, but not retention.

As with prior knowledge, the implementation of user control might vary for efficiency vs. effectiveness. If the goal is to improve effectiveness, then users might be able to increase the amount of content available to maximize their knowledge of a domain. If training efficiency is the goal, then learners might be able to determine the training needed to reach the required proficiency level with the least effort.

5.2.3. Difficulty Level and Adaptive Instruction

Difficulty level is also defined at three levels (high, moderate, and low). The author can elect to tag questions or other content to allow a GIFT-based tutor to select content based on learner performance state. This meta-data tagging supports adaptation to match learner competence and content difficulty (see Vygotsky's Zone of Proximal Development; Figure 4).

5.2.4. Content Type and Adaptive Instruction

Content type ranges from animations and graphics to text to video to visual content and may be somewhat redundant with IMI level adaptations, but allows GIFT authors to target and link specific types of media (e.g. video, audio, text, animations) with learner attributes.

5.2.5. Example Type and Adaptive Instruction

Finally, GIFT provides authors with two example types: case studies and worked examples. Case studies present criteria for solving problems and making decisions, and then the learner is given one or more example cases to exercise their decision making. Worked examples allow authors to present problems in a fully worked form and gradually reduce the sequence of the problem, process, or scenario so more information is provided by the learner over time.

5.3. Using Meta-data in GIFT Tutors

As content is added to a GIFT course, it is labeled with one or more of the metadata attributes described previously in Section 5.2. This allows rules in the pedagogical configuration where eMAP is the default to determine what type of content to select for the learner based on their assessed state. Developing new rules is a simple three step process as follows:

- Step 1: In which quadrant will the metadata be used? Since GIFT's theoretical instructional basis is Merrill's (1983) Component Display Theory (CDT), each learner state is assessed in the context of four instructional quadrants: rules, examples, recall, or practice.
- Step 2: Which state must the learner be in to use the metadata? This is a long list of learner attributes that include grit, learner ability, learning style, goal orientation, engagement, and several emotional states. One is selected from a dropdown list along with a state classification (high, medium, low, or unknown).
- Step 3: Which metadata attributes should be used? In this step the author selects from a dropdown list of metadata attributes (content descriptors) as noted above.

This allows the author to link content and adapt content based on changing learner states. Again, a critical element in this process is the accurate classification of learner states. Anything that interferes with data to support classification or affects the accuracy of the classification affects the effectiveness and efficiency of the tutor, and this in turn limits opportunities to improve learning capacity or accelerate learning.

6. CHALLENGES AND NEXT STEPS

A major challenge is to balance acceleration vs effectiveness. For example, if we accelerate learning how do optimize deep learning which usually requires high numbers of cycles and/or long periods of time for learning to set? How might we optimize multiple outcomes like rapid learning, high retention and high rate of skill transfer? Finally, how do we develop authoring tools that allow designers and developers to easily choose the appropriate design features to achieve these goals?

A next step will be to use the experimental testbed within GIFT to analyze learner attributes, adaptive instructional methods, and content to develop methods to balance instructional outcomes as shown in Figure 5 (Hanks, Pollack, and Cohen 1993).

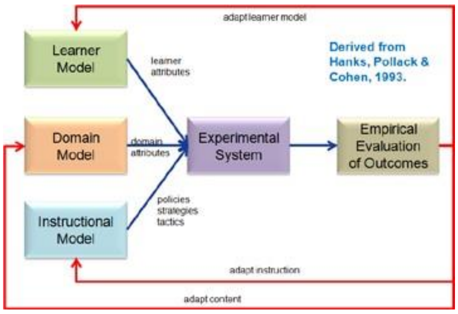

Figure 5: GIFT Evaluation Testbed

Another challenge to accelerating learning is optimizing complex decisions made by the tutor. The ability to make these instructional decisions rapidly is of some importance, but a more impactful capability will be highly effective decisions made by the ITS. This will reduce the amount of time used by the learner interacting with the tutor in activities that are not relevant or influential to learning outcomes. The basic research challenge is to optimize complex instructional decisions which involve multi-dimensional conditions of both the learner (e.g., states/traits) and the environment (e.g., entities, events, options) to select actions that influence learning and the desired outcome of "reducing time to proficiency". Meeting this challenge will likely involve solving other problems including:

- modeling complexity in individuals and teams as systems
- understanding the variability of human traits and behaviors and their relationship to learning

The modeling of the complexity of teams as systems will require investigation into teamwork as an antecedent to team learning and performance. Sottilare et al (2017) developed a model of team learning and performance based on a large scale meta-analysis of the team and tutoring literature. This provides a few initial steps in being able to manage the instruction of teams efficiently. As part of understanding human variability, the potential exists to gain some efficiency and effect through augmentation of learners. While this augmentation could take many forms, it could be as simple as understanding the relationship between learning capacity and the physical well-being of the learner. Research that shows exercise as a method for regulation of emotions (Salmon 2001; Karoly et al 2005), the association of fitness with enhanced fluid intelligence (Hillman, Erickson & Kramer 2008), and connection between exercise and executive attention (Kubesch et al 2009) might be applied in future ITSs to improve learner capacity and reduce "lost" time during instruction.

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