# CHAPTER 6 –Understanding Current Learner Modeling Approaches

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## Introduction

We've learned in the previous section some of the fundamental limitations and challenges that surround learner modeling development. However, this section continues to provide insight on these challenges and design recommendations for GIFT based on a current perspective of learner modeling tools and methods. As the core module of an ITS, the learner model is a representation of the learner's state of knowledge at any given time. Ideally, this model would be comprehensive enough to include and analyze information on the learner's individual difference characteristics as well as past, current, and predicted competencies, performance, cognition, affect, behaviors, etc. This model would also be flexible enough to support a variety of learning/instructional activities and types of learners. Realistically, such a model does not exist among current learner modeling research.

## Current State of Learner Modeling Research

Based on the previous section of this book, we observe that learner models are built for different purposes, such as recognizing solutions paths, evaluating problem-solving abilities, or describing constraints for violations made by the learner. Current techniques of generating learner models include Bayesian networks, belief networks, case-based reasoning, and expectation maximization. Methods such as model-tracing are more cost-effective, but do not have the ability to record or monitor learner's behavior. Learner models are commonly classified according to their relationship to an expert model, but can be classified by their performing function (i.e., corrective, elaborative, strategic, diagnostic, predictive, or evaluative).

The content within learner models is usually categorized in two components: domain-specific or domain-independent information (learner-specific characteristics/individual differences). 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. 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; and personal control beliefs (including general self-efficacy; locus of control).

First-generation ITS implementations primarily adapted instruction based on learner performance and current state of knowledge domain-specific information. These systems used learner models with corrective or elaborative functionality, but lacked any strategic, diagnostic, or predictive capabilities. The advantage of modeling this type of information is that it allows the model to be more generalized across multiple populations. Although useful, such information alone is not sufficient enough for providing the highly adaptive individualized training needed for ITSs of the next generation. Learner characteristics can be significantly different between learners and, collectively, is not the same for any two learners.

Primary sub-research areas of current learner modeling include, but are not limited to, learner state classifications, cognitive modeling, affect modeling, the impact of individual differences, behavioral and physiological sensing, and performance assessments. As the demand for higher adaptation and flexibility of learner models increases, so does the necessity to understand the interrelationship between all aspects of learner modeling content and assessment accuracy. Within the past 10 years, learner model research has extended to consider a broader range of learner characteristics as difficulty in addressing learner's knowledge gaps has become more apparent. Since the beginning, the learner modeling research community continues to help address this two-part question: *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?* Therefore, we can observe an increase in studies blending the sub-areas of learner modeling research as well as the emergence of other key areas of student modeling research, i.e., motivation, disengagement, metacognition, self-regulated learning, open learner modeling, group and collaborative learner modeling, and long-term learner modeling.

These newer areas of research present their own challenges in addition to the ones already surrounding the general research area. Some of these areas are covered in a later section of this book; however, the purpose of this section is to present the "bridge" to a new era of learner modeling research. The five chapters of this section discuss current areas and challenges surrounding learner modeling. Each chapter presents its own voice to a particular area of interest and gives recommendations on how GIFT can use the information within the chapter to enhance future GIFT versions.

The chapter by Tomar and Nielsen, entitled *Affective-Behavioral-Cognitve (ABC) Learner Modeling,* presents a framework for modeling interlocutors (i.e., users of e-learning systems) that integrates inductive and abductive reasoning over observations including the interlocutors' past and current behavior to develop a joint model for predicting their emotions, behaviors, and cognitive states. Their Affective-Behavioral-Cognitive (ABC) Learner Model follows an approach that users' behavioral responses can be a path to predict, recognize, and interpret their affective state. These behavioral responses are analyzed using a cognitive theory of emotions, which gives us inferences about the possible affective states of the learner. An appraisal component of the model relies on the desirability of events based on the learners' objectives, the affective and cognitive states predicted to result from the events, and the consequent expected behaviors. They discuss the specific aspects of their model and the interrelationship between these elements; provide an example of how the model can perform within an e-learning scenario; and highlight recommendations for how GIFT can use such a model for its learner modeling approaches.

The chapter by Holden and Sinatra, entitled *The Need for Empirical Evaluation of Learner Model Elements*, highlight issues with the lack of standardization on the structure of learner models and modeling techniques as it inhibits the validation and reusability of learner model elements. They argue that there are several aspects of user modeling, of which learner modeling is a subset, which have yet to be explored by the ITS learner modeling community. Such factors include learner's expertise, skills, attitudes, perceptions, and self-efficacy toward both computers/technology in general and the specific ITS. As we progress toward extending ITSs to be inclusive of job-related training and education, these factors may prove important in classificating learners' states, performance, and system behaviors. They also argue that more empirical evaluations are essential to better understanding the impact and interaction effects of current and potential learner model elements. Practical implications for researchers as well as design recommendations for such evaluations in GIFT are provided within this chapter.

The chapter by Hu, Morrison, and Cai, entitled *On the Use of Learner Micromodels as Partial Solutions to Complex Problems in a Multi-agent, Conversation-based Intelligent Tutoring System*, argues that at some point a general-purpose system, like GIFT, would employ an open, multi-agent architecture in which some agents will perform simple tasks, while others will take on more complex ones, such as generating appropriate responses to user questions. They describe an autonomous software agent that produces turn-by-turn analysis of a user's discourse moves on two dimensions: *novelty* and *relevance*. This process includes building a "*micromodel*" of the learner's current state, including a relevance-novelty measure for single turns and a series of turns. They provide an example of a highly specialized agent within a currently existing multi-agent, conversation-based ITS architecture that is capable of making assertions about the learner micromodel information that is of value to other agents and/or for their own purposes.

The chapter by Douglass, entitled *Learner Models in the Large-Scale Cognitive Modeling Initiative*, presents an Air Force Research Laboratory (AFRL) research effort to develop training capabilities for live, virtual, and constructive systems, as such system face challenges of (1) increasing the scale of cognitive models and (2) integrating them into software-intensive training environments. The AFRL Large-Scale Cognitive Modeling (LSCM) initiative is developing solutions to these scale and interoperability challenges based on high-level languages for describing cognitive models and net-centric simulation frameworks supporting them. This chapter introduces the LSCM initiative and explains how learner models are represented and used in the systems developing in its scope. The author illustrates how formal models of behavior models are specified and used to track events and build/refine representations of the knowledge, conceptual weaknesses, and procedural skills of monitored learners. He also explains how performance prediction and optimization capabilities based on mathematical extensions of the General Performance Equation (Anderson & Schunn, 2000) monitor learner actions, trace models of behavior, and use knowledge about learners to track and predict performance.

After reading these chapters, we can see that the lack of consensus and standardization for developing learner models is still apparent just as in the previous book section. We are now at the point of which such research can no longer ignore the necessity of building and enhancing standards for creating learner models with higher-level functionality to fulfill the *ideal* vision previously mentioned. Each of the chapters within this section provides a suggested method for aiding GIFT's future learner model design and functionality. Tomar and Nielsen, emphasize the importance of assessing the interplay between learner's cognition, affect, and behavior. Holden and Sinatra, emphasize the possibility of GIFT's ability to do comparison between learner model elements to support the validation of impact and interactions between learner characteristics. The last two chapters provide explicit examples and implementations of work-in-progress. Hu, Morrison, and Cai propose the use of multi-agents and micromodels as advantageous for reusability, a key element and motivation of GIFT. Moreover, Douglass highlights similarities between AFRL's LSCM and ARL's GIFT and views the use of research modeling language (RML) intelligent agents to effectively use behavior models to trace trainee's actions as beneficial to include within GIFT's design.

## Recommendations for GIFT's Immediate Direction

Each of the chapters within this section provided recommendations for GIFT in regards to its learner modeling approaches. In sum, they are as follows:

1. GIFT should consider incorporating the ABC model to observe learner performance over a period of time and to create affective and cognitive profiles which have threshold values and decay rates associated with the states in consideration. This process will allow GIFT's learner model to determine states more effectively.

2. Future learner modeling researchers should consider using GIFT for their research since the system provides plans to have the ability to interchange and learner models and its elements. Therefore, researchers will be able to understand how learner-specific characteristics,

perceptions, and preferences interplay and influence the learning process as well as how they dynamically change throughout instruction.

3. GIFT should consider adopting a common agent communication language (ACL) as the bases for a new generation of agent-based intelligent learning systems that are capable of autonomous cooperation. The instantiation of a common ACL and the development of a shared ontology can bring great benefits to GIFT's ultimate vision.

4. Integration of AFRL's LSCM/RML and ARL's GIFT would be an advantageous system that could serve as a technical solution to the problem of monitoring trainee actions and delivering contextually relevant instruction.

## References

Anderson, J.R. & Schunn, C. D. (2000). Implications of the ACT-R learning theory: No magic bullets. In R. Glaser (Ed.), *Advances in instructional psychology: Educational design and cognitive science (Vol. 5),* (pp. 1-34). Mahwah, NJ: Erlbaum.