Examining Elements of an Adaptive Instructional System (AIS) Conceptual Model

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Abstract. This paper examines the components, functions, and interactions of adaptive instructional systems (AISs) as a method to construct a conceptual model for use in the development of IEEE standards. AISs are *artificially-intelligent, computer-based systems that guide learning experiences by tailoring instruction and recommendations based on the goals, needs, and preferences of each individual learner or team in the context of domain learning objectives*. IEEE is exploring standards and best practices for AIS modeling, interoperability, and evaluation under its Project 2247 and affiliated working group. This paper was composed to document the interaction of learners with AISs in the context of a domain of instruction. The goal is to identify key interactions within AISs that drive instructional decisions, and to identify the data and methods required to support those machine-based instructions. In other words, we seek to identify methods to assess learner/team progress toward instructional objectives (e.g., knowledge, acquisition, skill development, performance, retention, and transfer of skills from instruction to operational/working environments. As part of the examination of AIS elements, we review a set of popular AIS architectures as a method of identifying what makes AISs unique from other instructional technologies. We conclude with recommendations for future AIS research and standards development.

Keywords: Instructional decisions · Learner data · Learner interaction · Learner states

1 Introduction

Adaptive instructional systems (AISs) come in many forms with the most common being the intelligent tutoring system: a computer-based system that automatically provides real-time, tailored, and relevant feedback and instruction to learners [1, 2]. Other forms include intelligent mentors (recommender systems) which promote the social relationship between learners and intelligent agents [3] and other intelligent media used for instruction. The common components of AISs include a domain model, a learner model, an instructional model, and an interface model [4].

During the last year, an IEEE working group chartered through Project 2247 has taken on the task of developing standards and best practices for AISs. This IEEE

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working group will be debating what is and is not an AIS. To date, the group has identified three potential areas for standardization: (1) a conceptual model for AISs, (2) interoperability standards for AISs, and (3) evaluation of best practices for AISs. This paper examines the development of an AIS conceptual model.

A conceptual model is a representation of a system composed of a set of concepts which are used to support understanding of the principles, functions, and interactions of the system it represents [5]. According to Kung and Solvberg [6], a successful conceptual model should satisfy four fundamental objectives:

- Enhance an individual's understanding of the representative system
- Facilitate efficient conveyance of system details between stakeholders
- Provide a point of reference for system designers to extract system specifications
- Document the system for future reference and provide a means for collaboration.

2 Defining AISs

We begin by defining AISs, examining the definition in detail to understand the drivers of adaptation, and then providing examples of popular AIS architectures and relate each to our chosen AIS definition. AISs are defined as: *artificially-intelligent, computer-based systems that guide learning experiences by tailoring instruction and recommendations based on the goals, needs, and preferences of each individual learner or team in the context of domain learning objectives* [7]. In examining our definition of AISs, we note that key words and phrases separate AISs from other classes of systems.

2.1 Artificially-Intelligent, Computer-Based

The phrase *artificially-intelligent, computer-based* indicates that we are discussing a system that is adaptive to changing conditions (and likely also adaptable). While both adaptive and adaptable systems provide system flexibility, adaptive systems are able to observe the environment, identify changing conditions, and then take action without human intervention [8]. In adaptable systems, the control over change/flexibility is in the hands of the user [8]. Many methods of adaptation have been used in AISs and these range from complex, real-time, autonomous decision-making to simple, prescriptive rules or decision trees.

2.2 Guided Learning Experiences

The phrase *guided learning experiences* indicates that we are discussing an intelligent system where the guide or tutor helps align learning with focused learning objectives. Learning is the process of acquiring new, or modifying existing, knowledge, behaviors, skills, values, or preferences [9]. Learning theories attempt to describe how learners acquire, process, and retain knowledge during learning while also accounting for various influences on the learning process: memory, emotions, prior experience, and environmental factors. While there are many approaches to learning, guided learning activities in AISs are usually *behavioral*, *cognitive*, *constructive*, *experiential* or *social/collaborative*, but it should be understood that these approaches are not mutually exclusive.

Behavioral learning approaches propose that learning is a long-term change in observable behavior in response to stimuli presented during instruction [10] and is primarily concerned with measurable results. Much of the game-based instruction today is intended to stimulate and reinforce performance and decision-making. Behavioral reinforcement may be positive (e.g., increased scoring or status, rewards) or negative (e.g., declining health status).

Cognitive learning is a process where the acquisition of knowledge results from the internal processing of information as it is transferred from a knowledgeable individual to the learner [11]. Cognitive approaches propose that learning is moderated by factors such as memory, engagement, motivation, fatigue, thinking, and reflection, and are also concerned with instructional methods leading to retention of knowledge. In AISs, we could expect to see activities where the learner is asked to reason (e.g., complete a task, solve a problem).

Constructive learning is a process where learning results in the development of mental models as part of a construction process where learners develop new ideas and concepts from their own knowledge and experience [12]. Constructive strategies include reflective thinking [13], learning by doing or experimentation [14], and discovery learning [15] which enable learners to construct mental models that have individual meaning with the goal that they take ownership of their learning. In AISs, scenario-based instruction offers opportunities for learners to explore their environment, expand their situational awareness (build their mental model), and then act on the environment in order to solve a problem or optimize a decision.

Experiential learning is a process of learning through experience [16], and combines aspects of behavioral, cognitive, and constructive learning. Specifically, Kolb's theory of experiential learning is a cycle of four stages: concrete experience, reflective observation, abstract conceptualization, and active experimentation [16]. In AISs, the same four stages may be implemented to support knowledge/skill acquisition, practice, reflection, modifying mental models, and then beginning anew.

Social/collaborative learning is a learning approach where learners are able to socially interact with others (peers, instructors, and others) with the goal of expanding their knowledge and skill [17]. Collaborative learning reinforces active participation by learners in the group, generally focusing on a learning goals and including computer-supported collaborative learning (CSCL) activities [18]. AISs have also been used to support collaborative learning, but AIS applications have been mainly concentrated on team training [19] and teamwork where "coordination, cooperation, and communication among individuals [is applied] to achieve a shared goal" [20].

2.3 Tailored Instruction and Recommendations

The phrase *tailored instruction and recommendations* indicates that AISs are learner-centric systems. Tailoring or adaptation in AISs is based on the goals, needs, and preferences of individual learners or teams. This close tie between actions by the AIS and the learner's states (e.g., knowledge, performance, emotion) and desired states (e.g., competency) form the basis of the learning effect model (LEM) [19, 21]. The LEM links learner data (e.g., physiological or behavioral data) to learner states (e.g., assessed or data-derived states—performance, proficiency or emotions) to instructional strategies (plans for action generated by the AIS) to instructional tactics (actions executed by the AIS). The terms *goals, needs,* and *preferences* also provide a temporal element to the AIS conceptual model in that they can be near-term (in the moment of instruction) or longer term as related to future desired states.

2.4 Context of Domain Learning Objectives

The phrase *context of domain learning objectives* indicates that AIS strategies and tactics are formulated with the goal of progressing toward specified learning objectives within a domain of instruction including team-based training [22]. It is important to note that a generalized AIS conceptual model would enable application to various domains of instruction. Already, AISs have been applied to cognitive domains such as mathematics [23], psychomotor domains such as marksmanship [24] and land navigation [25], and team/social/collaborative domains such as collaborative problem solving [26]. Next we examine decision making in AISs.

3 Examining Instructional Decisions in AISs

Key elements related to the AIS decision processes are learner proficiency (also known as prior knowledge) and context. Learner and domain data drive AIS decision making. In examining the automated instructional decision processes within AISs, we can distill them down into three simple types: recommendations, strategies, and tactics. *Recommendations* are relevant proposals that usually suggest possible next steps (e.g., problem or lesson selection) and fit into what VanLehn [27] describes as the outer loop of the tutoring process which executes once for each task, multi-step problem, or scenario.

As noted in our discussion of the LEM, *strategies* are plans for action by the AIS and *tactics* are actions usually executed by an AIS intelligent agent. Strategies and tactics are associated with the inner loop of the tutoring process which executes once for each step, turn, or action taken by the learner as they work toward a successful solution to a problem or scenario. During inner loop execution, feedback and/or hints may be provided to the learner during each step, turn or action, and the learner's developing competence is assessed and updated in the learner model. The learner states in the learner model are used by the outer loop to select a next task that is appropriate for that particular learner.

Intelligent agents are autonomous entities which observe their environment through sensors and act upon their environment using actuators while directing their activity towards achieving goals [28]. In AISs, Baylor [29] identifies three primary functions for intelligent agents: (1) ability to manage large amounts of data, (2) ability to serve as a credible instructional and domain expert, and (3) ability to modify the environment in response to learner performance. To this end, we add the requirement for the agent to be a learning agent, an entity that makes more effective decisions with each experience.

As shown in Fig. 1, intelligent agents in AISs observe and act on both the learner and the domain model (also known as the environment). The agents learn by reviewing the effectiveness of their decisions and updating policy when appropriate.

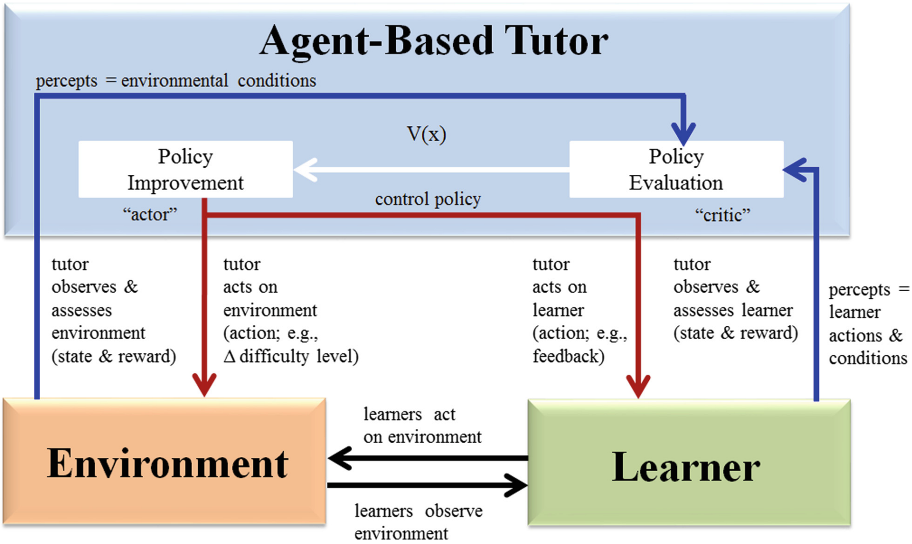

Fig. 1. Decision making process in AISs

We have discussed how models of the learner and the domain (environment) along with intelligent agents observing and acting on the instructional model support decision making in AISs. A critical element feeding the AIS decision process is the learner model with both real-time and historical data. Next we will examine how the AIS interface model also contributes real-time data from the learner to support state assessment.

4 Examining Learner–AIS Interaction

As noted earlier, a common element in AISs is an interface model, but the model and the data on which it acts are anything but standard. AIS interfaces can take many forms from simple dashboards for mathematics tutors to scenario-based virtual environments for instructing military tactics. The AIS uses the interface model to push and pull learner data to/from external environments. The notion of an external environment as part of an AIS may be transparent to the learner. The learner interacts with a computer program in the form of a simulation, a game, a webpage, or some other media as part of their instructional experience. The learner selects controls, moves avatars through simulated terrain, solves mathematical problems, or receives content from these media we are calling a domain or environment.

This interaction results in the generation of data that can be used by the AIS to assess the learner's progress toward assigned learning objectives. Referring back to Fig. 1, we see the learner acting on the environment and observing its response. The intelligent agent is also observing and acting on the environment and the learner to assess conditions and learner states respectively. Depending on the AIS and the tasks to be learned in the domain of instruction, the learner could be interfacing through controls or through natural modes with the aid of sensors. These interfacing paradigms include:

- Passive sensing of visual or other stimuli—this is the most common mode and usually involves presentation of content to the learner.
- Unobtrusive sensing of non-verbal learner behaviors—sensors are used to acquire the location, position, or gestures of the learner.
- Haptic interaction of the learner with environment—the learner interacts with the environment through a sense of touch facilitated by technology (e.g., haptic glove or controller).
- Natural language interaction with other entities—learners talk to human or virtual instructors or other learners.
- Text-based interaction with other entities—learners chat with human or virtual instructors or other learners.

Each of the modes noted above provide data to the AIS for decision making resulting in recommendations, strategies, or tactics. For data coming from outside of the AIS architecture, a mechanism must be provided to allow for both the transport and the decoding of that data. Transport means the movement of data outside the architecture to where it can be processed by the AIS. This is usually facilitated by a gateway. The decoding of the data so it can be understood and used by the AIS is usually accomplished via a define condition class that describes the format and establishes a variable name for each type of data.

Now that we have reviewed learner interfaces in AISs, we move on to review a few common AIS forms and associated architectures in the next section.

5 AIS Forms and Exemplar AIS Architectures

AISs take many forms and have many features (e.g., natural language dialogue or open learner models), but AISs can be categorized broadly as follows:

- Cognitive or Model Tracing AISs
- Example Tracing AISs
- Constraint-based Model AISs.

5.1 Cognitive or Model Tracing AISs

In model tracing systems, the AIS uses a cognitive model to trace the learner's steps as they move through the problem-solving process. This enables the AIS to provide step-by-step feedback to the learner as part of the inner loop of adaptive instruction [27].

Cognitive models attempt to represent domain knowledge in the same manner in which knowledge is represented in the human mind [30]. According to Adaptive Control of Thought—Rational (ACT-R) cognitive architecture [31] "acquiring cognitive knowledge involves the formulation of thousands of rules relating task goals and task states to actions and consequences" [32]. Thereby, model tracing is very process centric with the AIS attempting to comprehend the process that a learner uses to solve a problem and ultimately arrive at a solution. Model tracing AISs are composed of expert rules, buggy rules, a model tracer and a user interface. Expert rules represent the steps that a proficient or ideal learner might take to solve the problem [33].

Examples of cognitive or model tracing AISs include:

- Cognitive Tutor [34]—various tutors authored using the Cognitive Tutor and associated tools including GeneticsTutor and MathTutor
- Dragoon [35]—an intelligent tutoring system used to teach the construction and exploration of models of dynamic systems for use in mathematics and science.

5.2 Example Tracing AISs

Example tracing AISs, also called pseudo-tutors, are actually a subset of cognitive AISs, but have a much simpler cognitive model and use generalized examples of problem-solving behavior as opposed to model-tracing AISs which use a rule-based cognitive model to interpret learner behavior. An advantage of example-tracing AISs is that they can be built quickly without formal computer programming knowledge, and can serve as a tool for "rapid prototyping", or creating iterative prototypes over a short amount of time.

Examples of example tracing AISs include:

- Tuning Tutor [36]—an example-tracing tutor developed to teach learners about applied machine learning and specifically how to apply general principles of avoiding overfitting in cross-validation to the case where parameters of a model need to be tuned
- ASSISTment Builder [37]—a tool designed to rapidly create, test, and deploy a simple type of pseudo-tutors called ASSISTments which have a simple cognitive model based upon a state graph designed for a specific problem.

5.3 Constraint-Based AISs

Per Mitrovic and colleagues [38], constraint-based AISs use constraints to represent correct knowledge related to pedagogically significant states in order to eliminate the need to model the learner's misconceptions. A constraint is linked to set of solution states that share the same domain concept. Constraints are composed of three elements:

- Relevance Condition—describes when the constraint is applicable.
- Satisfaction Condition—specifies assessments to be applied to ascertain the correctness of the solution.

- Feedback Message—communicates with the learner to advise them that their solution is incorrect and why it is incorrect, and provides reminders to the learner of corresponding declarative knowledge.

An example constraint for a land navigation (orienteering) task might be *"when using a compass in the northern hemisphere, place the compass on your map and rotate the maps until the needle points to the top of the map"*. In this case the relevance condition is using a compass in the northern hemisphere. The satisfaction condition is the needle pointing to the top of the map. The feedback message might be to continue rotating until the needle points to the top of the page. Modeling of the learner is facilitated by assessments of the satisfaction or violation of constraints related to the domain concepts experienced.

Examples of constraint-based AISs include:

- Java Language Acquisition Tile Tutoring Environment (J-LATTE) [39]—a constraint-based intelligent tutoring system that teaches a subset of the Java programming language.
- POSIT Constraint-Based Tutor [40]—Process-oriented subtraction interface for tutoring.

5.4 Multi-domain AIS Architectures

The above AIS types (i.e., cognitive or model tracing, example tracing, and constraint-based) focus primarily on single domains. Now we move on to multi-domain architectures which, as the name suggests, are able to author, deliver, and automatically manage adaptive instruction in different educational and training domains. In addition to the Cognitive Tutor discussed above, we review three multi-domain architectures in this section:

- Generalized Intelligent Framework for Tutoring (GIFT)
- AutoTutor
- Active Student Participation Inspires Real Engagement (ASPIRE).

Generalized Intelligent Framework for Tutoring (GIFT)

The Generalized Intelligent Framework for Tutoring (GIFT), developed by the Learning in Intelligent Tutoring Environments (LITE) Lab at the US Army Research Laboratory, is emerging as a multi-domain, open source tutoring architecture [41, 42]. GIFT is a research prototype intended to reduce the computer skills and cost required to author ITSs, deploy them, manage them, and continuously evaluate the adaptive instruction they provide. A major advantage of GIFT is that three of its four functional elements are reusable across task domains. GIFT may also be linked to external training environments (e.g., serious games or virtual and augmented reality simulations) through a standardized gateway. GIFT authoring tools require no formal knowledge of computer programming or instructional design to develop effective ITSs. GIFT is freely available and may be hosted either locally or cloud-based. GIFT-based tutors have been prototyped to support training in adaptive marksmanship, land navigation, medical casualty care, and other military and non-military domains. GIFT, like other ITS technologies, has focused on training individuals, but research is underway to create tools and methods to support tutoring of collectives. At the time of this writing, GIFT has a community of over 2000 government, academic, and industry users in 76 countries. Additional information about GIFT is available at www.GIFTtutoring.org.

AutoTutor

AutoTutor, developed at the University of Memphis, has been a stalwart in dialogue-based tutoring over the last 20 years. AutoTutor is an intelligent tutoring system that holds conversations with the human learner in natural language. AutoTutor has produced learning gains across multiple domains (e.g., computer literacy, physics, critical thinking). AutoTutor research is focused on three main areas: human-inspired tutoring strategies, pedagogical agents, and natural language tutoring. AutoTutor has been applied to several task domains in support of one-to-one tutoring, and it has a comprehensive set of authoring tools and services. An emerging capability in AutoTutor is the trialogue, intelligent pedagogical agents that help students learn by holding a conversation in natural language between the student, a virtual instructor, and a virtual student peer [43]. Additional information about AutoTutor is available at www.autotutor.org/.

Active Student Participation Inspires Real Engagement (ASPIRE)

ASPIRE, developed by the University of Canterbury in New Zealand, is a system for developing and delivering adaptive instruction on the web [44]. The system consists of ASPIRE-Author, a tutor development server, and ASPIRE-Tutor, a tutoring server that delivers the resulting ITSs to students for guided instruction. The authoring system provides a unique process for composing an ontology of the domain by outlining basic domain concepts, their properties, and the relationships between concepts forming the basis of an expert model. Lessons learned from the ASPIRE authoring process may reduce the time and cost associated with authoring ITSs and/or increase the accuracy of the represented domain. Additional information about ASPIRE is available at http://aspire.cosc.canterbury.ac.nz/.

6 Next Steps—Recommendations for AIS Research and Standards Development

We presented and dissected a definition of AISs that addresses the functional interaction of their four common components. We explored AIS forms and discussed the characteristics AIS architectures to identify their commonalities, and compare and contrast their differences. As noted throughout this paper, AIS complexity and diversity of form present a challenge to developing standards. A conceptual model will provide the essential ontology and terms of reference for members of the AIS research, development and standards community to rally around. We conclude that difficult work is ahead in the development of a comprehensive AIS conceptual model, but that the development of this model is an essential step towards identifying AIS standards for interoperability and reuse.

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