Adaptive Technologies

Valerie J. Shute

Diego Zapata-Rivera

Research &
Development

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Valerie J. Shute and Diego Zapata-Rivera

ETS, Princeton, NJ

Abstract

This paper describes research and development efforts related to adaptive technologies, which can be combined with other technologies and processes to form an adaptive system. The goal of an adaptive system, in the context of this paper, is to create an instructionally sound and flexible environment that supports learning for students with a range of abilities, disabilities, interests, backgrounds, and other characteristics. After defining key terms and establishing a rationale for adaptation, we present a general framework to organize adaptive technologies. We then describe experts' thoughts on what to adapt and how to adapt and conclude with a summary of key challenges and potential futures of adaptive technologies.

Key words: Adaptivity, learner model, soft technologies, hard technologies

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Introduction

Air conditioning systems monitor and adjust room temperature, and cruise control systems monitor and adjust vehicle speed. Similarly, adaptive educational systems monitor important learner characteristics and make appropriate adjustments to the instructional milieu to support and enhance learning. In this paper we describe research and development related to adaptive technologies, which can be combined with other technologies and processes to form an adaptive system.

The goal of an adaptive system, in the context of this paper, is to create an instructionally sound and flexible environment that supports learning for students with a range of abilities, disabilities, interests, backgrounds, and other characteristics. The challenge of accomplishing this goal depends largely on accurately identifying characteristics of a particular learner or group of learners—such as type and level of knowledge, skills, personality traits, and affective states—and then determining how to leverage the information to improve student learning (e.g., Conati, 2002; Park & Lee, 2003, in press; Shute, Lajoie, & Gluck, 2000; Snow, 1989, 1994).

After defining key terms and establishing a rationale for adaptation, we present a general framework to organize adaptive technologies. We then describe experts' thoughts on (a) the variables to be taken into account when implementing an adaptive system (i.e., what to adapt) and (b) the best technologies and methods to accomplish adaptive goals (i.e., how to adapt). We conclude with a summary of key challenges and future applications of adaptive tools and technologies. Challenges include (a) obtaining useful and accurate learner information on which to base adaptive decisions, (b) maximizing benefits to the learner while minimizing costs associated with adaptive technologies, (c) addressing issues of learner control and privacy, and (d) figuring out the bandwidth problem, which has to do with the amount of relevant learner data that can be acquired at any time by the system.

Definitions

Before we begin our discussion on adaptive technologies that support learners in educational settings, we briefly define relevant terms. Most generally, to *adapt* means an adjustment from one situation or condition to another (e.g., software programs and persons are capable of adaptation). *Technology* refers to the application of science (methods or materials, such as electronic or digital products or systems) to achieve a particular objective, like the

enhancement of learning. A *system* in this context refers to a network of related computer software, hardware, and data transmission devices.

An *adaptive system* adjusts itself to suit particular learner characteristics and needs of the learner. *Adaptive technologies* help achieve this goal and are typically controlled by the computational devices, adapting content for different learners' needs and sometimes preferences. Information is usually maintained within a *learner model (LM)*, which is a representation of the learner managed by an adaptive system. LMs provide the basis for deciding how to provide personalized content to a particular individual and may include cognitive as well as noncognitive information. LMs have been used in many areas, such as adaptive educational and training systems (e.g., intelligent tutoring systems), help systems, and recommender systems.

Adaptive systems may consist of hard or soft technologies (e.g., devices vs. algorithms). *Hard technologies* are devices that may be used in adaptive systems to capture learner information (e.g., eye-tracking devices) and thus can be used to detect and classify learners' performance data or affective states such as confusion, frustration, excitement, and boredom. Hard technologies also can be used to present content in different formats (e.g., tactile tablet to accommodate visual disabilities). *Soft technologies* represent algorithms, programs, or environments that broaden the types of interaction between students and computers. For instance, an adaptive algorithm may be employed in a program that selects an assessment task or learning object most appropriate for a learner at a particular point in time.

The effectiveness of adaptive technologies hinges on accurate and informative student or learner models. For the remainder of this paper we use the terms *student model (SM)* and *learner model (LM)* interchangeably. Because this paper focuses on the educational functions of adaptive systems, we limit our modeling discussion to the context of *students* or *learners*, rather than more broadly defined *users*.

Rationale for Adapting Content

The attractiveness of adaptive technologies derives from the wide range of capabilities that these technologies afford. As discussed, one capability involves the real-time delivery of assessments and instructional content that adapt to learners' needs or preferences. Other technology interventions include simulations of dynamic events, extra practice opportunities on emergent skills, and alternative multimedia options—particularly those that allow greater access to individuals with disabilities.

We now provide evidence that supports the importance of adapting content to students to improve learning. These arguments concern individual and group differences among students.

Differences in incoming knowledge, skills, and abilities. The first reason for adapting content to the learner has to do with general individual differences in relation to incoming knowledge and skills among students. These differences are real, often large, and powerful. However, our educational system's traditional approach to teaching is not working well in relation to the diverse population of students in U.S. schools today (see Shute, 2006). Many have argued that incoming knowledge is the single most important determinant of subsequent learning (e.g., Alexander & Judy, 1988; Glaser, 1984; Tobias, 1994). Thus, it makes sense to assess students' incoming knowledge and skills to provide a sound starting point for teaching.

A second reason to adapt content to learners has to do with differences among learners in terms of relevant abilities and disabilities. The latter addresses issues of equity and accessibility. To illustrate, a student with visual disabilities will have great difficulty acquiring visually presented material, regardless of prior knowledge and skill in the subject area. Student abilities and disabilities usually can be readily identified and content adapted to accommodate the disability or to leverage an ability to support learning (Shute, Graf, & Hansen, 2005).

Differences in demographic and sociocultural variables. Another reason to adapt content to learners relates to demographic and sociocultural differences among students, which can affect learning outcomes and ultimately achievement (e.g., Conchas, 2006; Desimone, 1999; Fan & Chen, 2001). Adaptive technologies can help reduce some major gaps that persist in the United States (e.g., differential access to information and other resources). For instance, some researchers (e.g., C. E. Snow & Biancarosa, 2003) have argued that the achievement gap in the United States is largely due to differential language proficiencies. In response to this need, adaptive technologies that support English language learners are being developed (e.g., Yang, Zapata-Rivera, & Bauer, 2006).

Differences in affective variables. In addition to cognitive, physical, and sociocultural differences, students differ in relation to affective states—many of which influence learning— such as frustration, boredom, motivation, and confidence (e.g., Conati, 2002; Craig, Graesser, Sullins, & Gholson, 2004; Ekman, 2003; Kapoor & Picard, 2002; Litman & Forbes-Riley, 2004; Picard, 1997; Qu, Wang, & Johnson, 2005). Various noninvasive measures infer learners' states and alter the instructional environment to suit different needs. For instance, sensory input

systems detect, classify, and analyze learners' facial expressions (Yeasin & Bullot, 2005), eye movements (Conati, Mertin, Muldner, & Ternes, 2005), head position (Seo, Cohen, You, & Neumann, 2004), body posture and position (Chu & Cohen, 2005), gestures (Kettebekov, Yeasin, & Sharma, 2003), and speech (Potamianos, Narayanan, & Riccardi, 2005). Bayesian networks and other statistical classifier systems can render the inferences about states from a variety of inputs (e.g., excessive fidgeting implying inattention).

In summary, there are a number of compelling reasons to adapt content to learners. We now provide context and coherence for adaptive technologies using a general four-process model. This model has been extended from a simpler two-process model that lies at the heart of adaptive technology—diagnosis and prescription—and from a process model to support assessment (Mislevy, Steinberg, & Almond, 2003).

Four-Process Adaptive Cycle

The success of any adaptive technology to promote learning requires accurate diagnosis of learner characteristics (e.g., knowledge, skill, motivation, persistence). The collection of learner information then can be used as the basis for the prescription of optimal content, such as hints, explanations, hypertext links, practice problems, encouragement, metacognitive support, and so forth.

Our framework involves a four-process cycle connecting the learner to appropriate educational materials and resources (e.g., other learners, learning objects, applications, and pedagogical agents) through the use of a LM (see Figure1). The components of this four-process cycle are (a) capture, (b) analyze, (c) select, and (d) present.

Capture. The capture process entails gathering personal information about the learner as he or she interacts with the environment, depicted in Figure 1 by the larger human figure. Relevant information can include cognitive as well as noncognitive aspects of the learner. This information is used to update internal models maintained by the system.

Analyze. The analyze process requires the creation and maintenance of a model of the learner in relation to the domain, typically representing information in terms of inferences on current states. In Figure 1, this is depicted as the smaller human figure (i.e., the SM).

Select. Information (i.e., content in the broadest sense) is selected according to the model of the learner maintained by the system and the goals of the system (e.g., next learning object or test item). This process is often required to determine how and when to intervene.
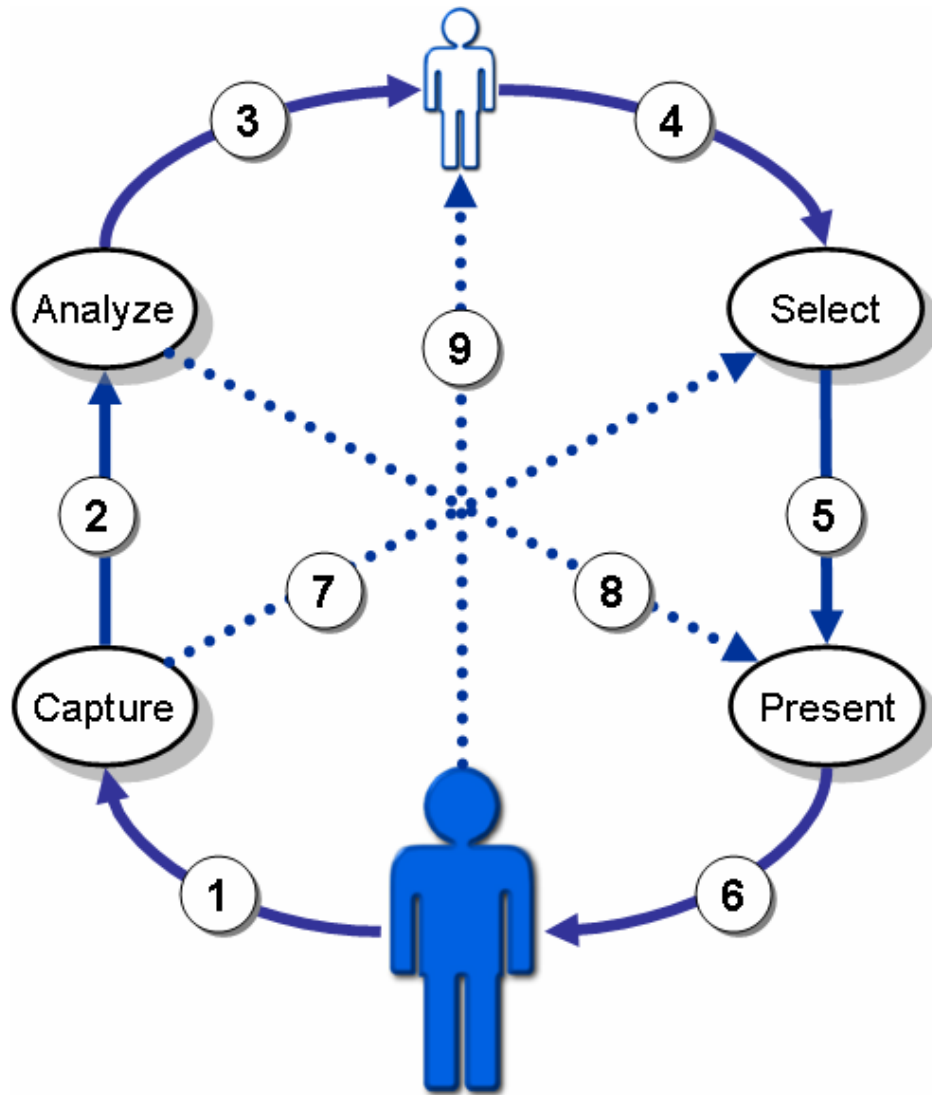
Figure 1. **Four-process adaptive cycle.**

Present. Based on results from the select process, specific content is presented to the learner. This entails appropriate use of different media, devices, and technologies efficiently to convey information to the learner.

This model accommodates alternative scenarios. Table 1 describes some of these scenarios that involve different types of adaptation, starting with a completely adaptive cycle and continuing to a nonadaptive presentation.

Figure 2 depicts the evolving nature of the four-process adaptive loop. That is, as time passes, the LM becomes more refined and accurate—represented in Figure 2 by different degrees of saturation.

Table 1

Scenarios Represented in the Four-Process Adaptive Cycle Depicted in Figure 1

Scenario	Description
A complete cycle (1, 2, 3, 4, 5, and 6)	All processes of the cycle are exercised: capturing relevant information, analyzing it, updating the variables that are modeled in the LM, selecting appropriate learning resources and strategies that meet the current needs of the learner, and making them available to the student in an appropriate manner. This cycle will continue until the goals of the instructional activity have been met.
Modifying the adaptive cycle (1, 2, 3, 4, 5, 6, and 9)	The learner is allowed to interact with the LM. The nature of this interaction and the effects on the LM can vary (e.g., overwriting the value of a particular variable). Allowing human interaction with the model may help reduce the complexity of the diagnostic and selection processes by decreasing the level of uncertainty inherent in the processes. It also can benefit the learner by increasing learner awareness and supporting self-reflection.
Monitoring path (1, 2, and 3)	The learner is continuously monitored; information gathered is analyzed and used to update learner profiles (e.g., homeland security surveillance system, analyzing profiles of individuals for risk-analysis purposes). This path can be seen as a cycle that spins off to a third party instead of returning to the learner.
Short (or temporary) memory cycle (1, 7, 5, and 6)	The selection of content and educational resources is done by using the most recent information gathered from the learner (e.g., current test results and navigation commands). No permanent LM is maintained. Adaptation is performed using information gathered from the latest interaction between learner and the system.
Short (or temporary) memory, no selection cycle (1, 2, 8, and 6)	A predefined path on the curriculum structure is followed. No LM is maintained. This predefined path dictates which educational resources and testing materials are presented to the learner.

Note. LM = learner model.
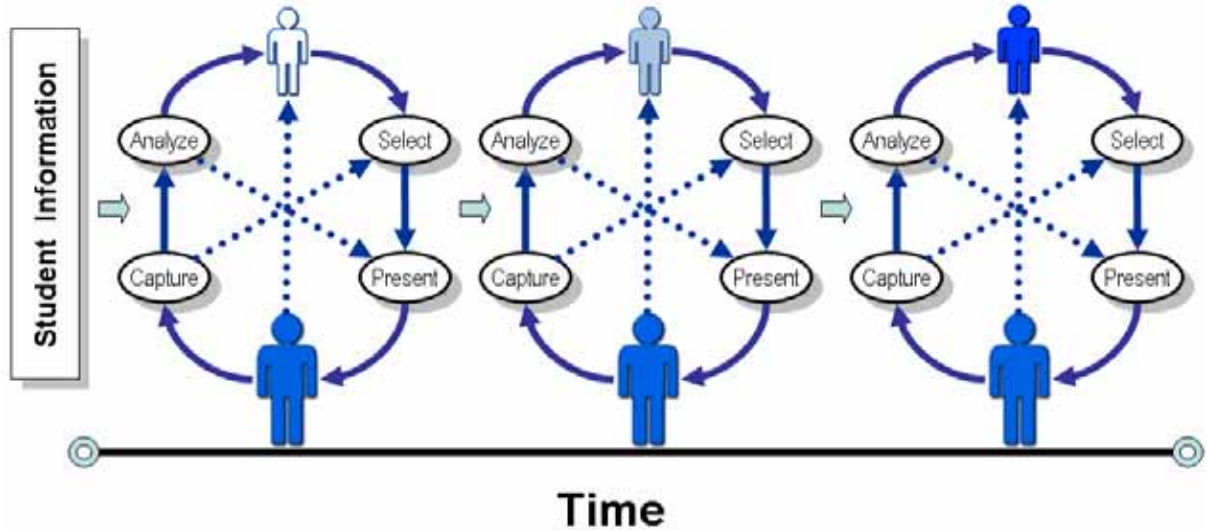
Figure 2. **Flow of diagnosis and adaptation over time.**

In general, the architecture of adaptive applications has evolved in a way that reflects the evolution of software systems architecture. For example, it is possible to find *standalone* adaptive applications where the complete adaptive system—including its SM—resides in a single machine. There are also adaptive applications that have been implemented using a *distributed* architecture model. Some examples of distributed applications include (a) client-server adaptive applications that make use of SM servers and shells (see Fink & Kobsa, 2000), (b) distributed agent-based platforms (Azambuja Silveira, &Vicari, 2002; Vassileva, McCalla, & Greer, 2003), (c) hybrid approaches involving distributed agents and a SM server (Brusilovsky, Sosnovsky, & Shcherbinina, 2005; Zapata-Rivera & Greer, 2004), (d) peer-to-peer architectures (Bretzke & Vassileva, 2003), and (e) service-oriented architectures (Fröschl, 2005; González, Angulo, López, & de la Rosa, 2005; Kabassi & Virvou, 2003; Trella, Carmona, & Conejo, 2005; Winter, Brooks, & Greer, 2005).

To illustrate how our four-process adaptive model can accommodate more distributed scenarios, Figure 3 depicts an extended version of our model, which includes a group of agents—application, personal, and pedagogical. Each agent maintains a personal view of the learner. LM information and educational resources can be distributed in different places. Agents communicate with each other directly or through an LM server to share information that can be used to help the learner achieve individual learning goals.
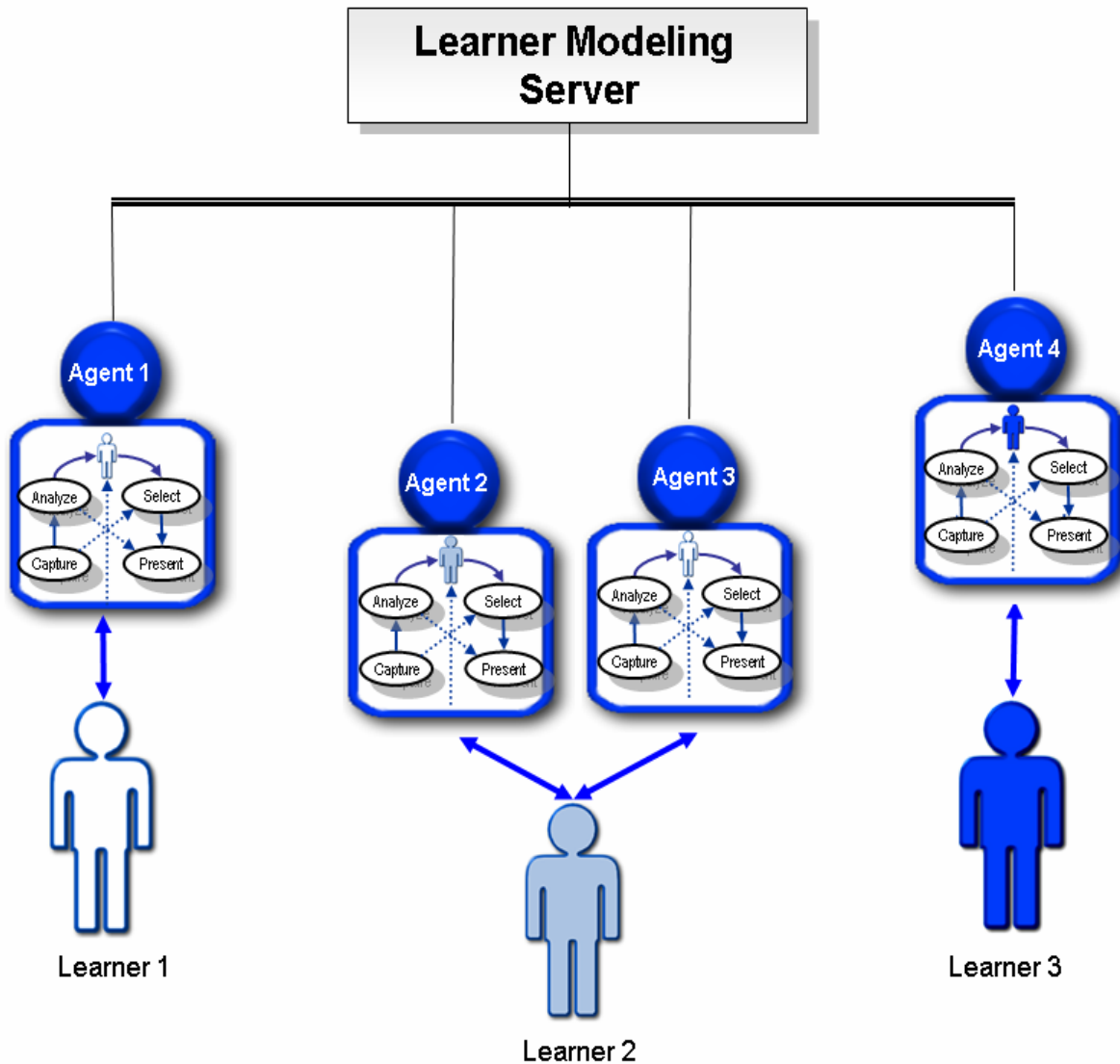
Figure 3. **Communication among agents and learners.**

Summary of Current Adaptive Technologies

This section describes adaptive technologies currently in use and relevant to the context of this review. The technologies have been divided into two main sections: soft and hard technologies. As described earlier, this distinction may be likened to programs versus devices and may be used across the array of processes described in the previous section (i.e., capturing student information, analyzing it, selecting content, and presenting it).

The technologies selected for inclusion in this section are those that are formulated to make use of, to some extent, a LM. Also, this listing is intended to be illustrative and not

exhaustive. For a more thorough description of adaptive technologies in the context of electronic learning (e-learning) systems, see Fröschl (2005), Kobsa (in press), Jameson (2006), and Buxton (2006)—the latter for a directory of sources for input technologies.

Figure 4 depicts examples of both soft and hard technologies (in shaded boxes) operating within an adaptive learning environment in relation to our four-process adaptive cycle. For example, technologies for *analyzing* and *selecting* LM information include Bayesian networks and machine learning techniques. Moreover, these technologies are examined in relation to both learner variables (cognitive and noncognitive) and modeling approaches (quantitative and qualitative). Similarly, examples of soft and hard technologies are provided for the processes of capturing and presenting information.

Soft Technologies

Soft technologies represent programs or approaches that capture, analyze, select, or present information. Their primary goals are to create LMs (diagnostic function) or to utilize information from LMs (prescriptive function).

Quantitative modeling. In general, quantitative modeling of learners obtains estimates about the current state of some attributes. This involves models and datasets as well as typically complex relationships and calculations. To begin modeling, relationships are established and tested, in line with a hypothesis that forms the basis of the model and its test. To quantify the relationships, graphical models can be used to create graphs of the relationships and statistical models can define quantitative equations of expected relationships to model uncertainty (for more, see Jameson, 1995).

Qualitative modeling. Qualitative modeling supports learners by constructing conceptual models of systems and their behavior using qualitative formalisms. According to Bredeweg and Forbus (2003), qualitative modeling is a valuable technology because much of education is concerned with conceptual knowledge (e.g., causal theories of physical phenomena). Environments using qualitative models may use diagrammatic representations to facilitate understanding of important concepts and relationships. Evaluations in educational settings provide support for the hypothesis that qualitative modeling tools can be valuable aids for learning (e.g., Fredericksen & White, 2002; Leelawong, Wang, Biswas, Vye, & Bransford, 2001).

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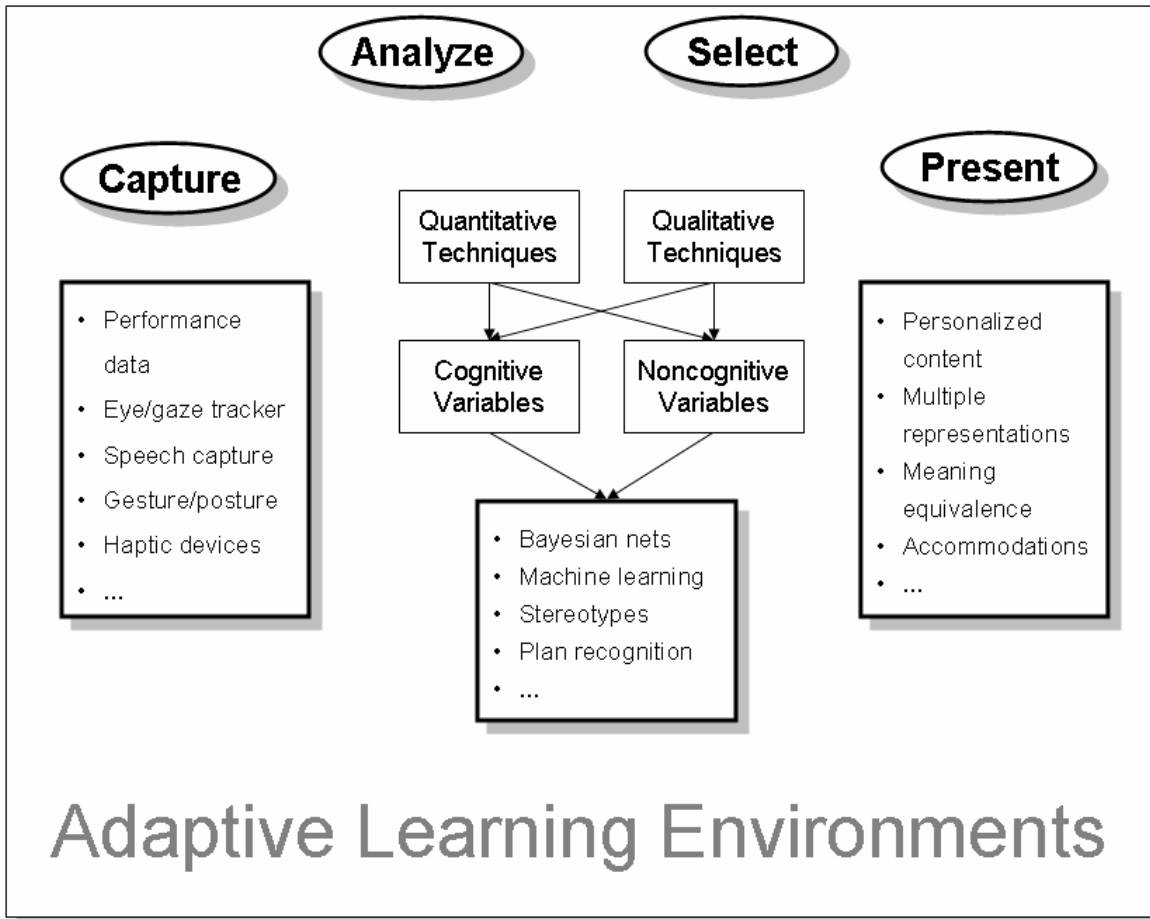
Figure 4. **Overview of technologies to support learner modeling.**

Cognitive modeling. Cognitive models may be quantitative or qualitative. They help predict complex human behavior, including skill learning, problem solving, and other types of cognitive activities. Generally, cognitive models may apply across various domains, serve different functions, and model well- or ill-defined knowledge (e.g., design problems). The range of cognitive modeling approaches includes, for example, symbolic, connectionist, hybrid, neural, probabilistic, and deterministic mathematical models. Probably the best known examples of cognitive models come from the cognitive tutoring research by John Anderson and colleagues (e.g., Anderson, 1993; Anderson, Boyle, Corbett, & Lewis, 1990; Anderson, Corbett, Koedinger, & Pelletier, 1995; Anderson & Lebiere, 1998; Koedinger & Anderson, 1998; Koedinger, Anderson, Hadley, & Mark, 1997; Matsuda, Cohen, & Koedinger, 2005).

Machine learning. Machine learning methods applicable for LM include rule or tree (analogy) learning methods, probabilistic learning methods, and instance- or case-based learning approaches. A learner model can take advantage of machine learning methods and thus increase accuracy, efficiency, and extensibility in areas not modeled before (Sison & Shimura, 1998). According to Webb, Pazzani, and Billsus (2001), machine learning methods can be used to model (a) cognitive processes underlying the learner's actions, (b) differences between the learner's skills and expert skills, (c) the learner's behavioral patterns or preferences, and (d) other characteristics of the learner.

Bayesian networks. Bayesian networks (Pearl, 1988) are related to the machine learning methods (see above) and are used within LMs to handle uncertainty by using probabilistic inference to update and improve belief values (e.g., regarding learner proficiencies). The inductive and deductive reasoning capabilities of Bayesian nets support "what-if" scenarios by activating and observing evidence that describes a particular case or situation and then by propagating that information through the network using the internal probability distributions that govern the behavior of the Bayesian net. Resulting probabilities inform decision making as needed, for instance, in our select process. Examples of Bayesian net implementations for LMs can be seen in Conati, Gertner, and VanLehn (2002); Shute et al. (2005); and VanLehn et al. (2005).

Stereotype methods. A stereotype is a collection of frequently occurring characteristics of users (e.g., physical characteristics, social background, computer experience). Adaptive methods are used to initially assign users to specific classes (stereotypes) so that previously unknown characteristics can be inferred on the basis of the assumption that they will share characteristics with others in the same class (see Kobsa, in press). Creating stereotypes is a common way of user modeling, whereby a small amount of initial information is used to assume a large number of default assumptions. When more information about individuals becomes available, the default assumptions may be altered (Rich, 1979). There are two types of stereotyping: fixed and default. In fixed stereotyping, learners are classified according to their performance into a predefined stereotype that is determined by, for instance, an academic level. Default stereotyping is a more flexible approach. At the beginning of a session, learners are stereotyped to default values, but as the learning process proceeds and learner performance data are obtained, the settings of the initial stereotype are gradually replaced by more individualized settings (see Kay, 2000).

Overlay methods. An overlay model is a novice–expert difference model representing missing conceptions, often implemented as either an expert model annotated for missing items or an expert model with weights assigned to each element in the expert knowledge base. One of the first overlay models used the program WUSOR (Stansfield, Carr, & Goldstein, 1976). Current applications of this overlay approach has been used in a variety of research projects, such as Kay (1999), Vassileva (1998), and Zapata-Rivera and Greer (2000).

Plan recognition. A plan is a sequence of actions to achieve a certain goal and reflects the learner's intentions and desires. Plan recognition is based on observing the learner's input actions, and then the system inferring all possible learner plans based on the observed actions. According to Kobsa (1993), two main techniques are used to recognize the learner's plan: (a) establishing a *plan library* containing all possible plans, where the selection of the actual plan is based on the match between observed actions and a set of actions in the library, and (b) *plan construction*, where the system controls a library of all possible learner actions combined with the effects and the preconditions of these actions. Possible next actions can be calculated by comparing the effects of preceding actions with the preconditions of actions stored in the actions library. To read more about applying plan recognition techniques in relation to instructional planning efforts, see Kobsa (1993) and Vassileva and Wasson (1996).

Cumulative or persistent SM. The cumulative SM represents the more traditional approach, where the SM is analyzed and updated in response to the learner's activities. This involves building a SM that captures and represents emerging knowledge, skills, and other attributes of the learner, with the computer responding to updated observations with modified content that can be minutely adjusted. The selection and presentation of subsequent content is dependent on individual response histories (see Shute & Psotka, 1996; VanLehn et al., 2005; Wenger, 1987).

Temporary SM. Temporary SMs usually do not persist in the system after the learner has logged out. In artificial intelligence, formalisms used to describe the world often face something called the *frame problem*, which is the problem of inferring whether something that was true is still true. For example, the accuracy of cumulative (or persistent) SMs can degrade as students forget information. Brooks (1999) and others have circumvented the frame problem by using the world as its own model (e.g., if you want to know if a window is closed, check the actual window rather than consult an internal model). The same idea applies to SM. That is, if you want

to know if a student can still multiply two fractions, ask the student to multiply two fractions. This is what human tutors do with their one-time students, yielding a SM that is always up-to-date and corresponds to the short memory cycle scenario shown in Table 1.

Pedagogical agents. Pedagogical means that these programs are designed to teach, and *agent* suggests that the programs are semiautonomous, possessing their own goals and making decisions on what actions to take to achieve their goals (i.e., a programmer has not predefined every action for them). The current generation of pedagogical agents is interactive and sometimes animated. For example, students can speak to agents that speak back, and agents often have faces and bodies, use gestures, and can move around a computer screen. Some well-known agents include the following: Steve (e.g., Johnson & Rickel, 1997; Johnson, Rickel, & Lester, 2000); AutoTutor (e.g., Graesser, Person, & Harter, & the Tutoring Research Group, 2001); Adaptive e-Learning with Eye-Tracking (AdeLE) (Shaw, Johnson, & Ganeshan, 1999); and the Tactical Language Training System (Johnson et al., 2004).

An interesting application of agent technologies includes *teachable agents* that have been used successfully to promote student learning of mathematics and science (Biswas, Schwartz, Bransford, & the Teachable Agent Group at Vanderbilt, 2001). This computer-based environment involves a multiagent system (Betty's Brain) that implements a learning-by-teaching paradigm. Students teach Betty by using concept map representations with a visual interface. Betty is intelligent not because she learns on her own, but because she can apply qualitative-reasoning techniques to answer questions that are directly related to what she has been taught. Another class of agents are *emotional agents* (affective computing), which have been employed to support student learning (e.g., Picard, 1997; Wright, 1997). Motivating students and sustaining their motivation historically has been a major obstacle in education. Emotional (or affective) agents create a learning environment involving learners and interactive characters (or believable agents). Two important aspects of such characters are that they appear emotional and can engage in social interactions. This requires a broad agent architecture and some degree of modeling of other agents in the environment. Finally, pedagogical or virtual agents can collaborate with students, enabling new types of interactions and support for learning (e.g., Johnson et al., 2000).

Hard Technologies

In this section, we review several hardware-based technologies. These are mainly used for input (i.e., data capture) and presentation purposes.

Biologically based devices. Some bio-based devices were originally developed to support learners with disabilities (i.e., assistive technologies). However, many are being created or repurposed to support LMs, for both cognitive and noncognitive student data. For instance, obtaining information about where the learner is looking at the computer during learning provides evidence about the learner's current state or attentiveness (for good reviews of eye-tracking research, see Conati et al., 2005, and Merten & Conati, 2006). This information can inform the system about the next optimal path to take for this particular learner. In terms of eye-tracking technology, eye movements, scanning patterns, and pupil diameter are indicators of thought and mental processing that occurs during learning from visual sources (e.g., Rayner, 1998). Consequently, eye-tracking data can be used as the basis for supporting and guiding learners during the learning process. To illustrate the approach, consider the novel application of this eye-tracking technology within a system named AdeLE (e.g., García-Barrios et al., 2004). This introduces a real-time, eye-tracking procedure for intelligent user profile deduction as well as the use of a dynamic background library to support learning.

Speech-capture devices. These devices allow users to interact with the computer via speech, instead of relying on typing their input. Consequently, this approach is valuable for individuals with physical disabilities that preclude typing, for young children who cannot yet type, and so on. One example project using speech-capture technology is Project Literacy Innovation that Speech Technology Enables (LISTEN) by Mostow, Beck, and colleagues (as cited in Project LISTEN, 2005). This automated reading tutor displays stories on a computer screen and listens to children read aloud. It intervenes when the reader makes mistakes, gets stuck, clicks for help, or otherwise encounters difficulty (Project LISTEN, 2005).

Head-gesture capture devices. Many computers currently are equipped with a video camera. Processing the image provides a means to track head position and movement. Software by Visionics Corp, for example, provides this capability. Zelinsky and Heinzmann (1996) developed a system that can recognize 13 different head or face gestures. In addition, researchers in areas such as animated pedagogical and conversational agents have used sensors and a video

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camera for recognizing facial gestures. This information is used to facilitate human-agent interaction (e.g., Cassell, Nakano, Bickmore, Sidner, & Rich, 2001).

Assistive technologies. Disabilities and nonnative language status can be major obstacles to learning from a computer. Examining adaptations in light of a validity framework can be valuable if not essential for ensuring effectiveness (for more on this topic, see Hansen & Mislevy, 2005; Hansen, Mislevy, Steinberg, Lee, & Forer, 2005). An increasing number of sites on the Web contain information for persons with special needs. See the Special Needs Opportunity Window (SNOW, 2006) Web site for information about the different kinds of adaptive technologies for people with disabilities.

Adaptive Environments

When several technologies (soft and hard) are integrated into a single environment or platform to accomplish the goal of enhancing student learning via adaptation, this is called an adaptive environment. We now examine several well-known types of adaptive environments.

Adaptive hypermedia environment. Adaptive hypermedia systems (AHS) or environments are extended from an intelligent tutoring system foundation and combine adaptive instructional systems and hypermedia-based systems (see Brusilovsky, 1996). An AHS combines hypertext and hypermedia, utilizes features of the learner in the model, and applies the LM during adaptation of visible aspects of the system to the learner. Brusilovsky (2001) distinguished between two different types of AHS: (a) adapting the presentation of content (i.e., different media formats or orderings) and (b) adapting the navigation or learning path via direct guidance or hiding, reordering, annotating, or even disabling or removing links (Kinshuk & Lin, 2004).

Adaptive educational hypermedia environment. A particular type of AHS is an adaptive educational hypermedia system (AEHS). The hyperspace of AEHS is kept relatively small given its focus on a specific topic. Consequently, the focus of the LM is entirely on the domain knowledge of the learner (Brusilovsky, 1996). Henze and Nejdl (2003) have described AEHS as consisting of a document space, a LM, observations, and an adaptation component. The document space belongs to the hypermedia system and is enriched with associated information (e.g., annotations and domain or knowledge graphs). The LM stores, describes, and infers information, knowledge, and preferences about a learner. Observations represent the information about the interaction between the learner and the AEHS and are used for updating the LM.

Collaborative learning environment. An alternative approach to individualized learning is collaborative learning, the notion that students, working together, can learn more than by themselves, especially when they bring complementary, rather than identical, contributions to the joint enterprise (Cumming & Self, 1989). Collaboration is a process by which "individuals negotiate and share meanings relevant to the problem-solving task at hand" (Teasley & Roschelle, 1993, p. 229). Research in this area examines methods to accurately capture and analyze student interactions in collaborative or distance learning environments. For instance, Soller (2004) described different techniques (e.g., probabilistic machine learning) to model knowledge-sharing interactions among different learners.

Simulation and immersive environment. Simulations and immersive environments (e.g., virtual reality) change in response to specific user actions, but typically the change is not due to an underlying LM, but rather is a function of a predefined set of rules. However, some simulations and immersive environments do maintain a LM (e.g., Rickel & Johnson, 1997). For example, Smithtown (e.g., Shute & Glaser, 1990; Shute, Glaser, & Raghavan, 1989) is a simulated environment where students change parameters in the hypothetical town—such as per capita income, population, and the price of gasoline—and see immediate changes in various markets, thus learning the laws of supply and demand. Smithtown actually maintains two LMs: one to model students' microeconomic knowledge and skills and the other to model their scientific inquiry skills.

As we just have shown, many different programs and devices serve to capture, analyze, select, or present information to a learner based on current or perceived needs and wants. We now turn our attention to what some experts in the field have to say about adaptive technologies. Our goal is to provide additional perspectives on relevant topics.

Experts' Thoughts on Adaptive Technologies

To supplement our review of adaptive technologies, we asked leading adaptive-technology experts to address two questions: (a) What to adapt (i.e., what variables should be taken into account when implementing an adaptive system), and (b) how to adapt (i.e., what are the best technologies and methods that you use or recommend)? The experts who responded to our e-mail queries include Cristina Conati, Jim Greer, Tanja Mitrovic, Julita Vassileva, and Beverly Woolf.

What to Adapt?

Our experts responded to the what-to-adapt question in two ways: (a) input data or *learner variables* to be measured and used as the basis for adaptation and (b) output or *instructional variables* that adapt to learners' needs and occasionally to preferences. Table 2 summarizes their collective responses and illustrates a wide range of student variables and adaptive pedagogical responses.

Table 2

What to Adapt

Learner variables	Instructional variables
Cognitive abilities (e.g., math skills, reading skills, cognitive development stage, problem solving, analogical reasoning)	Feedback type (e.g., hints, explanations) and timing (e.g., immediate, delayed)
Metacognitive skills (e.g., self-explanation, self-assessment, reflection, planning)	Content sequencing (e.g., concepts and learning objects as well as tasks, items, or problems to solve)
Affective states (e.g., motivation, attention, engagement)	Scaffolding (e.g., support and fading as warranted, rewards)
Additional variables (e.g., personality, learner styles, social skills such as collaboration, and perceptual skills)	View of material (e.g., overview, preview, and review as well as visualization of goal or solution structure)

How to Adapt?

Responses to this question tended to focus on domain independent approaches and technologies based on analysis of student and pedagogical models. Table 3 lists the methods explicated by our experts, which represent innovative implementations of the adaptive technologies discussed in the *Current Adaptive Technologies* section.

In this section, we have presented a variety of learner traits and states that are judged relevant to modeling in educational contexts. In addition to these variables to be captured and analyzed in the LM, new data-mining technologies permit the discovery of even more learning variables for a more refined, just-in-time collection of student information. This will allow systems to discover new things about a learner based on multiple sources of information from a single learner as well as from different learners. This sets the stage for accomplishing more accurate individual modeling as well as distributed and collaborative learner modeling in the future. Challenges and envisioned futures are discussed next.

Table 3

How to Adapt

Adaptive approach	Rationale
Probability and decision theory	Rule-based approaches are typically used in adaptive systems, but using probabilistic learner models provides formal theories of decision making for adaptation. Decision theory takes into account the uncertainty in both model assessment and adaptation actions' outcome and combines it with a formal representation of system objectives to identify optimal actions (Conati, personal communication, May 18, 2006).
Constraint-based tutoring	The domain model is represented as a set of constraints on correct solutions, the long-term SM contains constraint histories, and these can be used to generate the system's estimate of students' knowledge. Constraint histories also can be used to generate a population SM (e.g., probabilistic model), which later can be adapted with the student's data to provide adaptive actions (e.g., problem or feedback selection) (Mitrovic, personal communication, May 17, 2006).
Concept mapping	In order to adapt content (e.g., sequences of concepts, learning objects, hints) to the student, employ a concept map with prerequisite relationships, an overlay model of the students' knowledge, and a reactive planning algorithm (Vassileva, personal communication, May 15, 2006).
Unsupervised machine learning	Most existing SMs are built by relying on expert knowledge, either for direct model definition or for labeling data to be used by supervised machine learning techniques. But, relying on expert knowledge can be very costly, and for some innovative applications such knowledge may be nonexistent. An alternative is to use unsupervised machine learning to build SMs from unlabeled data using clustering techniques for defining classes of user behaviors during learning environment interactions (Conati, personal communication, May 18, 2006).
Exploiting learning standards	Adapting around standardized content packages (e.g., IMS QTI, IEEE LOM) can make use (and reuse) of large quantities of high-quality content. This is done by extending the SCORM Runtime Environment specification to include user-modeling functionality. This permits content authors to take advantage of (and update) SMs in a content management system. Content recommendations to students are based on the SM, and recommendation is light-weight with minimal demands on content developers (Greer & Brooks, personal communication, May 16, 2006).
Analyzing expert teachers	Studying expert teachers and tutors is an invaluable source of information on how to adapt instructional content, but it is not always possible. Moreover, for some innovative systems (e.g., educational games) human tutors may not know how to provide effective pedagogical support. An alternative is to run so-called "Wizard of Oz" studies to test adaptation strategies defined via pedagogical or cognitive theories or through intuition (Conati, personal communication, May 18, 2006).
Matching instructional support to cognitive ability	Adapting instructional support to match students' cognitive needs (i.e., developmental stage and different abilities) has been shown to promote better learning in experimental studies (e.g., Arroyo, Beal, Murray, Walles, & Woolf, 2004; Arroyo, Woolf, & Beal, 2006). The rationale is that if students receive instructional support that they are not cognitively ready to use, it will be less effective in promoting learning (Woolf, personal communication, May 22, 2006).

Note. SM = student model.

Challenges and Future of Adaptive Technologies

There are several major obstacles to surmount for the area of adaptive technologies to move forward. As in the previous section, we augment this section by directly asking leading researchers in the field of adaptive technologies to summarize their views on challenges and the future of adaptive technologies. Our experts were Anthony Jameson, Judy Kay, and Gord McCalla.

Practical and Technical Challenges

The main barriers to moving ahead in the area of adaptive educational technologies are obtaining useful and accurate learner information on which to base adaptive decisions, maximizing benefits to learners while minimizing costs associated with adaptive technologies, addressing issues relating to learner control and privacy, and figuring out the bandwidth problem, relating to the scope of learner data. Each of these is now described.

Developing useful LMs. A core challenge of developing effective adaptive technologies is building useful LMs. According to Kay (personal communication, June 6, 2006), collecting meaningful learning traces (i.e., data obtained from records and student log files) should help overcome this challenge. That is, the large and increasing volume of learning trace data associated with individuals is generally trapped within logs of individual tools. Consequently, these data represent a wasted, untapped resource that might be used to build rich LMs. To transform learning trace data into a LM, a process must interpret the data to infer relevant learner attributes, such as knowledge and preferences. This would require the addition of a knowledge layer that maps learner trace data (evidence) to a set of inferences about the learner's knowledge.

Acquiring valid learner data. A related barrier to overcome involves the acquisition of valid learner data, particularly when accomplished via self-reports (Kay, personal communication, June 6, 2006). Self-report information has at least two problems. First, learners may enter inaccurate data either purposefully (e.g., based on concerns about privacy or a desire to present themselves in a flattering light) or by accident (e.g., lack of knowledge about the characteristics they are providing). This problem may be solved by maintaining separate views of the LM (e.g., the learner's view) and providing mechanisms for reconciling different views into one LM. Second, additional interactions required during the learning process (e.g., completing online questionnaires) increases the time imposition and can lead to frustration (Kay, personal

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communication, June 6, 2006) as well as to potentially invalid data from students simply trying to get to the content quickly (Greer & Brooks, personal communication, May 16, 2006). However, gathering such information not only can reduce the complexity of diagnosis, but also can encourage students to become more active participants in learning and to assume greater responsibility for their own LMs.

Maximizing benefits. Currently, the cost of developing and employing adaptive technologies is often quite high, while the return on investment is equivocal. This challenge is a practical one: how to maximize the benefit-to-cost ratio of adaptive technologies. Despite a growing number of adaptive technologies available today, there are too few controlled evaluations of the technologies and systems. According to Jameson (personal communication, May 24, 2006), addressing this problem should begin with the identification of specific conditions that warrant adaptation. There are at least two standards of comparison for adaptivity: (a) fixed sequencing and (b) learner control of content. The question is whether these comparison conditions accomplish the same goals that could be achieved via adaptation. Jameson (personal communication, May 24, 2006) has offered a strategy for finding appropriate adaptivity applications: Look for cases where the learner is in a poor position to self-select content. For instance, the learner may want to choose an item from a very large set of items whose properties he or she is not familiar with, and the learner may be in a situation lacking resources that would be required for effective performance.

Minimizing costs. One straightforward way to minimize the technical costs associated with adaptivity involves the use of more or less off-the-shelf technology for user adaptivity (e.g., Fink & Kobsa, 2000; Jameson, personal communication, May 24, 2006). Another cost-minimizing option suggested by Greer and Brooks (personal communication, May 16, 2006) involves leveraging existing content. They noted that adaptive algorithms are often domain specific, requiring the hand coding of content to fit the specific form of adaptation. With the growing use of standardized content management systems and content available with descriptive metadata, the adaptive learning community has the opportunity to get in on the ground floor in creating standards for content adaptation. Greer and Brooks's approach involves creating formal ontologies to capture content, context, and learning outcomes. Instances of these ontologies can be reasoned over by a learning environment to provide content (and peer help) recommendations.

Formal ontologies then can be shared (e.g., via Semantic Web specifications) and provide a clear set of deduction rules as well as extensive tool support.

Dealing with learner control issues. Learners often want to control their learning environment, thus one strategy that addresses this desire is to allow them partial control of the process. Jameson (personal communication, May 24, 2006) identified a number of ways to divide the job of making a learning-path decision by the system versus the learner (see Wickens & Hollands, 2000, chapter 13). For example, the system can (a) recommend several possibilities and allow the learner to choose from that list, (b) ask the learner for approval of a suggested action, or (c) proceed with a particular action but allow the learner to interrupt its execution of the action. Choosing the right point on this continuum can be just as important as ensuring high accuracy of the system's modeling and decision making.

Addressing privacy and obtrusiveness concerns. When a system has control of the learning environment and automatically adapts, its behavior may be viewed by learners as relatively unpredictable, incomprehensible, or uncontrollable (Jameson, 2006). Moreover, the actions that the system performs to acquire information about the learner or to obtain confirmation for proposed actions may make the system seem obtrusive or threaten the learner's privacy (Kobsa, 2002). According to Kay (personal communication, June 6, 2006), one way to address this concern is to build all parts of the LM system in a transparent manner, to ensure that the learner can scrutinize the system's data management and the way in which those data are interpreted (Cook & Kay, 1994).

Considering the scope of the LM. According to McCalla (personal communication, May 26, 2006), adapting to individual differences is essential to making adaptive systems more effective. While there is some support for this claim (e.g., Arroyo, Beal, Murray, Walles, & Woolf, 2004; Arroyo, Woolf, & Beal, 2006), significantly more experimental studies are needed. The traditional approach to achieving adaptivity has required the system to maintain a LM that captures certain characteristics of each learner and then to use those data as the basis for adapting content (Greer & McCalla, 1994). One major problem concerns obtaining sufficient bandwidth of learner interactions to allow the capture of a range of characteristics to paint an accurate picture of the learner for appropriate adaptation. Bandwidth in this case refers to the amount of relevant learner data that can be passed along a communications channel in a given period of time. The bad news is that it is difficult to maintain a consistent model, as learners' knowledge

and motivations change over time. The good news is that the bandwidth problem is diminishing as learners spend more time interacting with technology (McCalla, personal communication, May 26, 2006), thus it is possible to gather a broad range of information about them. Moreover, learners' interactions now can be recorded at a fine enough grain size to produce more depth in the LM. The maintenance problem may be addressed by the simple expedient of not trying to maintain a persistent LM, but instead making sense of a learner's interactions with an adaptive system just in time to achieve particular pedagogical goals.

Having summarized the main challenges surrounding adaptive technologies and possible ways to overcome them, we now present some visions of where the field may be heading in the future. We present these visions through the eyes of our three experts.

The Future of Adaptive Technology

Judy Kay's view. A long-term vision for adaptive technologies involves the design and development of lifelong LMs, under the control of each learner. This idea draws on the range of learning traces available from various tools and contexts. Learners could release relevant parts of their lifelong LM to new learning environments. Realizing such a vision requires that all aspects of the LM and its use are amenable to learner control. Part of the future for LMs of this type must include the aggregation of information across models. This relates back to two major challenges: privacy and user control of personal data, its use and reuse. An important part of addressing these issues will be to build LMs and associated applications so that learners always can access and control their LM and its use. This needs to go beyond just making the LM more open and inspectable to ensuring that learners actually take control of its use.

Gord McCalla's view. The next envisioned future of adaptive technologies relates to the ecological approach. The learning environment is assumed to be a repository of known learning objects, but both learning object and repository are defined broadly to include a variety of learning environments. To further enhance flexibility, the repository also may include artificial agents representing learning objects and personal agents representing users (e.g., learners, tutors, and teachers). In this vision, each agent maintains models of other agents and users, which help the agent to achieve its goals. The models contain raw data tracked during interactions between the agents and users (and other agents) as well as inferences drawn from this raw data. Such inferences are only made as needed (and as resources allow) while an agent is trying to achieve a pedagogical goal. This is called *active modeling* (see McCalla, Vassileva, Greer, & Bull, 2000).

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After a learner has interacted with a learning object, a copy of the model that the learner's personal agent has been keeping can be attached to the learning object. This copy is called a *learner model instance* and represents the agent's view of the learner during this particular interaction, both what the personal agent inferred about the learner's characteristics and how the learner interacted with the system. Over time, each learning object slowly accumulates LM instances that collectively form a record of the experiences of many different learners as they have interacted with the learning object. To achieve various pedagogical goals, agents can mine LM instances—attached to one or more learning objects—for patterns about how learners interacted with the learning objects. The approach is called *ecological* because the agents and objects in the environment continuously must accumulate information, allowing natural selection as to which objects are useful or not. Useless objects and agents thus can be pruned. Moreover, there may be ecological niches based on goals (e.g., certain agents and learning objects are useful for a given goal, whereas others are not). Finally, the whole environment evolves and changes naturally through interaction among the agents and ongoing attachment of LM instances to learning objects. The ecological approach will require research into many issues, such as experimentation to discover algorithms that work for particular kinds of pedagogical goals.

Anthony Jameson's view. Although many improvements can and should be made in terms of tools and techniques for adaptation, it is even more important to focus on the central problem of getting the benefits to exceed the costs. Adaptivity, like many other novel technologies, is a technology that is worthwhile, albeit within a restricted range of settings. It is thus critically important to identify clearly these settings and to solve the adaptation problems therein. The ultimate goal is to enhance (in the short or middle term) the usability and effectiveness of real systems in the real world.

Summary and Discussion

Adaptive systems will continue to evolve as new technologies appear in the field and old ones transform and become more established. The future of the field is wide open in that it can evolve in different ways. Such evolution will depend on factors such as the emergence of new technologies, new media, advances in learning, measurement, artificial intelligence, and general policies and standards that take hold (or not) in relation to adaptive instruction and learning.

One shift that we see as critically important to the field, particularly in the near term, is toward conducting controlled evaluations of adaptive technologies and systems. This will enable

the community to gauge the value-added of these often expensive technologies in relation to improving student learning or other valued proficiencies (e.g., self esteem and motivation). Our review has shed light on a range of technologies, but the bottom line has not yet been addressed: What works, for whom, and under which conditions and contexts?

We agree with Conati's assertion (personal communication, May 18, 2006) that learners' traits targeted for adaptation clearly should improve the pedagogical effectiveness of the system. This depends on whether (a) a given trait is relevant to achieve the system's pedagogical goals, (b) there is enough learner variability on the trait to justify the need for individualized interaction, and (c) there is sufficient knowledge on how to adapt to learner differences along this trait. Along the same lines, Jameson (personal communication, May 24, 2006) has argued that the benefits of adaptation should be weighed against the cost of modeling each candidate trait, to focus on traits that provide the highest benefit given the available resources.

A similar appeal for conducting controlled evaluations was made more than a decade ago, during the heyday of intelligent tutoring system development. Now, as then, the call for evaluations of adaptive technologies and systems is crucial for future development efforts to succeed in terms of promoting learning. Building adaptive systems and not evaluating them is like "building a boat and not taking it in the water" (Shute & Regian, 1993, p. 268). Evaluation not only is important to the future of the field, but also can be as exciting as the process of developing the tools and systems. Although results may be surprising or humbling, they always will be informative.

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