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Adaptive Technologies

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CONTENTS

ABSTRACT

This chapter 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 chapter, 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. We conclude with a summary of key challenges and potential futures of adaptive technologies.

KEYWORDS

Adaptivity: The capability exhibited by an organic or an artificial organism to alter its behavior according to the environment. In the context of an instructional system, this capability allows the system to alter its behavior according to learner needs and other characteristics. This is typically represented within a learner model.

Hard technologies: These represent devices may be used in adaptive systems to capture learner information (e.g., eye-tracking devices) or to present content to a learner (e.g., tactile tablet). These devices can be used to detect and classify learners' performance data or affective states such as confusion, frustration, excitement, disappointment, boredom, confidence, contentment, and so on.

Learner model: A representation of the learner that is maintained by an adaptive system. Learner models can be used to provide personalized instruction to a particular individual, and may include cognitive and noncognitive aspects of the learner. Learner models have been used in many areas, such as adaptive educational and training systems, help systems, recommender systems, and others.

Soft technologies: These are usually algorithms, programs, or even environments that broaden the types of interaction between students and computers; for example, an adaptive algorithm may be employed in a program that selects an assessment task that provides the most information about a particular learner at a particular point in time.

INTRODUCTION

Air-conditioning systems monitor and adjust room temperature; 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 chapter, 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 chapter, 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, affective states—and then determining how to leverage the information to improve student learning (Conati, 2002; Park and Lee, 2003; Shute et al., 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: (1) the variables to be taken into account when implementing an adaptive system (i.e., *what* to adapt), and (2) 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: (1) obtaining useful and accurate learner information on which to base adaptive decisions, (2) maximizing benefits to the learner while minimizing costs associated with adaptive technologies, (3) addressing issues of learner control and privacy, and (4) figuring out the bandwidth problem, which has to do with the amount of relevant learner data that can be acquired at any time.

Definitions

Before we begin our discussion on adaptive technologies that support learners in educational settings, we will briefly define relevant terms. Most generally, to *adapt* means making 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, electronic or digital products or systems) to achieve a particular objective, such as 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, which is a* representation of the learner managed by an adaptive system. Learner models provide the basis for deciding how to provide personalized content to a particular individual and may include cognitive as well as noncognitive information. Learner models 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 used in adaptive systems to capture learner information (e.g., eye-tracking devices), thus they can be used to detect and classify learners' performance data or affective states such as confusion, frustration, excitement, and boredom. Hard technologies can also be used to present content in various 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 example, 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 hinge on accurate and informative student or learner models. For the remainder of this chapter, we use the terms *student model* and *learner model* interchangeably, and abbreviate them as either SM or LM. Because this chapter 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 and 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 (Shute, 2006). Many have argued that incoming knowledge is the *single* most important determinant of subsequent learning (Alexander and 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 can usually be readily identified and content adapted to accommodate the disability or leverage an ability to support learning (Shute et al., 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 (Conchas, 2006; Desimone, 1999; Fan and 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 example, some researchers (see, for example, Snow and 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 (Yang et al., 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 (Conati, 2002; Craig et al., 2004; Ekman, 2003; Kapoor and Picard, 2002; Litman and Forbes-Riley, 2004; Picard, 1997; Qu et al., 2005). Various noninvasive measures infer learners' states and alter the instructional environment to suit different needs; for example, sensory input systems detect, classify, and analyze learners' facial expressions (Yeasin and Bullot, 2005), eye movements (Conati et al., 2005), head position (Seo et al., 2004), body posture and position (Chu and Cohen, 2005), gestures (Kettebekov et al., 2003), and speech (Potamianos et al., 2005). Bayesian networks and other statistical classifier systems can render 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 by way of a general four-process model. This model has been extended from (1) a simpler two-process model that lies at the heart of adaptive technology (diagnosis and prescription), and (2) a process model to support assessment (Mislevy et al., 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 can then 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 learner model (see Figure 24.1). The components of this four-process cycle include capture, analyze, select, and present.

Capture

This process entails gathering personal information about the learner as the learner interacts with the environment (depicted in Figure 24.1 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

This 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 24.1, this is depicted as the smaller human figure (i.e., the SM).
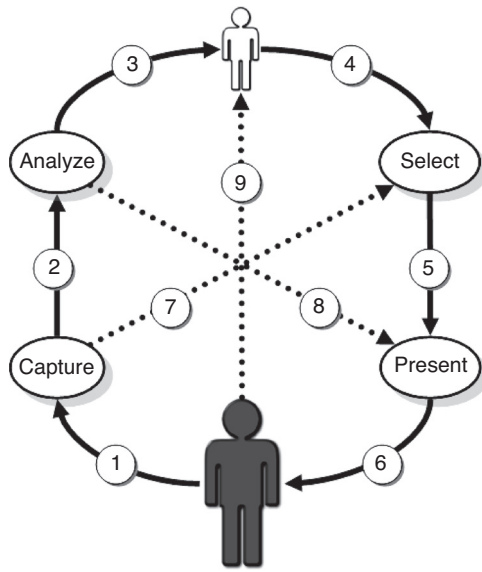
Figure 24.1 Four-process adaptive cycle.

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.

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 to

efficiently convey information to the learner. This model accommodates alternative scenarios. Table 24.1 describes some of these scenarios that involve different types of adaptation starting with a completely adaptive cycle and continuing to a nonadaptive presentation. Figure 24.2 illustrates the evolving nature of the four-process adaptive loop; that is, as time passes, the learner model becomes more refined and accurate, as represented in the figure by different degrees of saturation.

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 *stand-alone* adaptive applications where the complete adaptive system—including its student model—resides in a single machine. Also, adaptive applications have been implemented using a *distributed* architecture model. Some examples of distributed applications include: (1) client–server adaptive applications that make use of student modeling servers and shells (Fink and Kobsa, 2000); (2) distributed agent-based platforms (Azambuja et al., 2002; Vassileva et al., 2003); (3) hybrid approaches involving distributed agents and a student modeling server (Brusilovsky et al., 2005; Zapata-Rivera and Greer, 2004); (4) peer-to-peer architectures (Bretzke and Vassileva, 2003); and (5) service-oriented architectures (Fröschl, 2005; González et al., 2005; Kabassi and Virvou, 2003; Trella et al., 2005; Winter et al., 2005).

To illustrate how our four-process adaptive model can accommodate more distributed scenarios, Figure 24.3 depicts an extended version of our model, which includes a group of agents: application, personal, and pedagogical. Each agent maintains a personal view of

TABLE 24.1
Scenarios Represented in the Four-Process Adaptive Cycle

| 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, selecting appropriate 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 have been met.
Modifying the adaptive cycle (1, 2, 3, 4, 5, 6, and 9)	The learner is allowed to interact with the learner model. The nature of this interaction and the effects on the learner model can vary. Allowing human interaction with the model may reduce the complexity of the diagnostic and selection processes by decreasing uncertainty. It can also benefit the learner by increasing awareness and self-reflection.
Monitoring path (1, 2, and 3)	The learner is continuously monitored; information gathered is analyzed and used to update 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 (e.g., current test results and navigation commands). No permanent learner model 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 learner model is maintained. This predefined path dictates which educational resources and testing materials are presented to the learner.
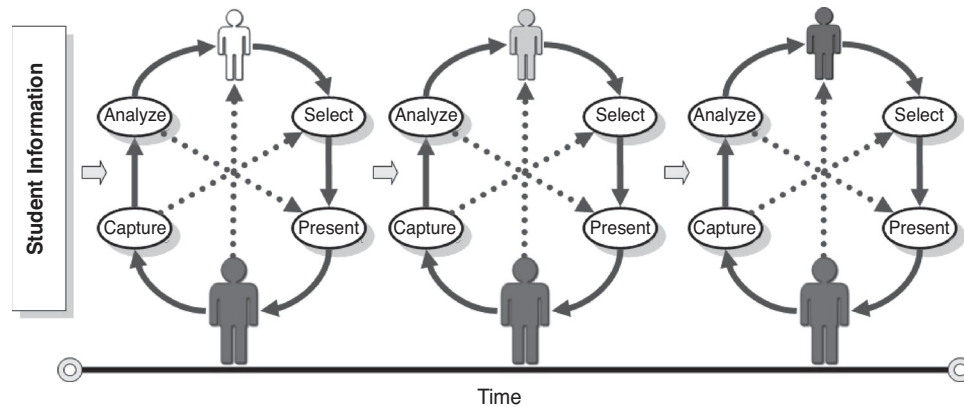
Figure 24.2 Flow of diagnosis and adaptation over time.

the learner. Learner model 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 learners achieve their learning goals.

SUMMARY OF CURRENT ADAPTIVE TECHNOLOGIES

This section describes adaptive technologies currently in use and relevant to the context of this chapter. The technologies have been divided into two main sections: soft and hard technologies. As described earlier, this distinction may be likened to *programs* vs. *devices*, respectively, 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 make use of, to some extent, a learner model in its formulation. Also, this listing is intended to be illustrative and not exhaustive. For a more thorough description of adaptive technologies in the context of e-learning systems, see Fröschl (2005), Kobsa (2006), Jameson (2006a), and Buxton (2006), the latter for a directory of sources for input technologies.

Figure 24.4 provides 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. 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) and to utilize information from LMs (prescriptive function).

Quantitative Modeling

In general, quantitative modeling of learners obtains estimates about the current state of some attribute. 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, one can use graphical models to create graphs of the relationships and statistical models that will 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 (Frederiksen and White, 2002; Leelawong et al., 2001).
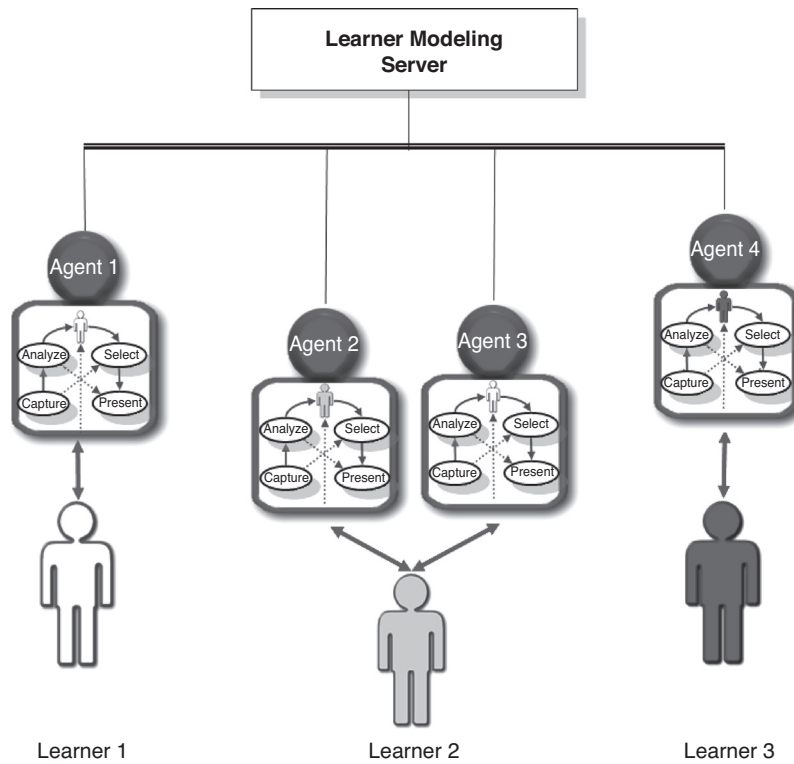
Figure 24.3 Communication among agents and learners.
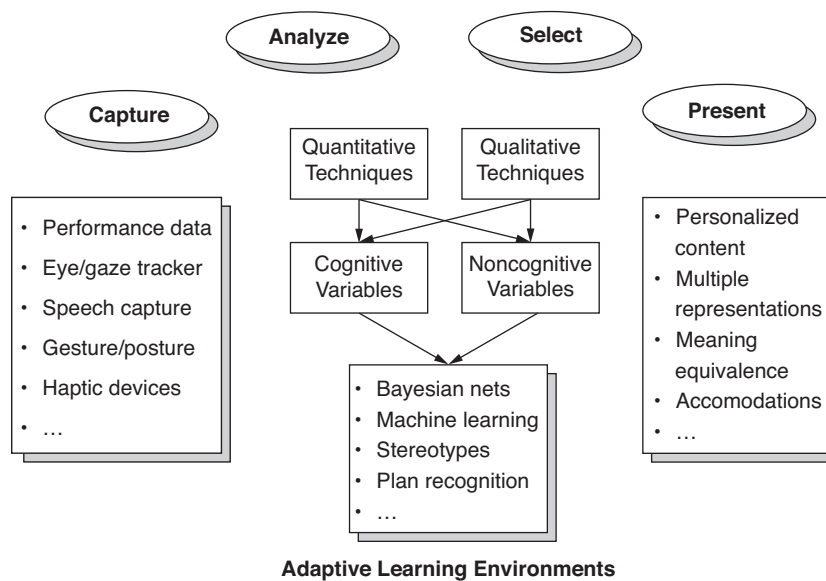
Figure 24.4 Overview of technologies to support learner modeling.

Cognitive Modeling

Cognitive models may be quantitative or qualitative. They help predict complex human behaviors, 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 exam-

ples of cognitive models come from the cognitive tutoring research by John Anderson and colleagues (Anderson, 1993; Anderson and Lebiere, 1998; Anderson et al., 1990, 1995; Koedinger and Anderson, 1998; Koedinger et al., 1997; Matsuda et al., 2005).

Machine Learning

Machine learning methods applicable for learner modeling include rule/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 and Shimura, 1998). According to Webb and colleagues (2001), machine learning methods can be used to model: (1) cognitive processes underlying the learner's actions, (2) differences between the learner's skills and expert skills, (3) the learner's behavioral patterns or preferences, and (4) other characteristics of the learner.

Bayesian Networks

Bayesian networks (Pearl, 1988) are related to the machine learning methods (see above) and are used within learner models 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 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 in, for example, our select process. Examples of Bayesian net implementations for LMs may be found in Conati et al. (2002), Shute et al. (2005), and VanLehn and colleagues (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 previously unknown characteristics can be inferred on the basis of the assumption that they will share characteristics with others in the same class (Kobsa, 2006). Creating stereotypes is a common approach to user modeling, whereby a small amount of initial information is used to assume a large number of default assumptions. When more informa-

tion about individuals becomes available, the default assumptions may be altered (Rich, 1979). The two types of stereotyping are *fixed* and *default*. In fixed stereotyping, learners are classified according to their performance into a predefined stereotype that is determined by, for example, 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 is obtained, the settings of the initial stereotype are gradually replaced by more individualized settings (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 uses of an overlay model was done with the WUSOR program (Stansfield et al., 1976). Current applications of this overlay approach can be found in a variety of research projects (Kay, 1999; Vassileva, 1998; Zapata-Rivera and Greer, 2000).

Plan Recognition

A plan is a sequence of actions to achieve a certain goal, and it reflects the learner's intentions and desires. Plan recognition is based on observing the learner's input actions and the system then 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: (1) 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 (2) *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 may 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 (1992).

Cumulative/Persistent Student Model

The cumulative student model represents the more traditional approach where the SM is analyzed and updated in response to the learner's activities. This

involves building a student model 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 (Shute and Psotka, 1996; VanLehn et al., 2005; Wenger, 1987).

Temporary Student Model

Temporary student models 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) student models can degrade as students forget things. Brooks (1999) and others have circumvented the frame problem by using the world as its own model (i.e., 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 student modeling; 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, and their one-time students yield a student model that is always up to date and corresponds to the short memory cycle scenario shown in Table 24.1.

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 can speak back, often have faces and bodies, use gestures, and can move around a computer screen. Some well-known agents include Steve (Johnson et al., 2000), AutoTutor (Graesser et al., 2001), AdeLE (Shaw et al., 1999), and the Tactical Language Training System (Johnson et al., 2004).

An interesting application of agent technologies is *teachable agents*, which have been successfully used to promote student learning of mathematics and science (Biswas et al., 2001). This computer-based environment involves a multi-agent 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 is *emotional agents* (affective computing), which have been employed to support student learning (Picard, 1997; Wright, 1997). Getting students motivated and sustaining their motivation have historically been major obstacles 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 (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 biologically based devices were originally developed to support learners with disabilities (i.e., assistive technologies); however, many are being created or repurposed to support learner models for both cognitive and noncognitive student data. As an example, obtaining information about where on the computer the learner is looking during learning provides evidence about the learner's current state and attentiveness (for good reviews of eye-tracking research, see Conati et al., 2005; Merten and Conati, 2006). This information can inform the system about what is 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 (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 a novel application of this technology known as AdeLE (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 LISTEN (Literacy Innovation that Speech Technology ENables), by Jack Mostow and colleagues. This is an automated reading tutor that 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 is likely to encounter difficulty (Project LISTEN, 2006).

Head-Gesture Capture Devices

Many computers currently are equipped with video cameras. 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 and face gestures. In addition, researchers in areas such as animated pedagogical and conversational agents have used sensors and a video camera for recognizing facial gestures. This information is used to facilitate human–agent interaction (Cassell et al., 2001).

Assistive Technologies

Disabilities and non-native 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 and Mislevy, 2005; Hansen et al., 2005). Currently, a growing number of sites on the web provide 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 environments or systems (AHSs) are extended from an intelligent tutoring system foundation and combine adaptive instructional systems and hypermedia-based systems (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: (1) adapting the presentation of content (i.e., different media formats or orderings), and (2) adapting the navigation or learning path, via direct guidance; hiding, reordering, or annotating links; or even disabling or removing links (Kinshuk and 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 learner model, observations, and an adaptation component. The document space belongs to the hypermedia system and is enriched with associated information (e.g., annotations, 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—that is, 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 and Self, 1989). Collaboration is a process by which "individuals negotiate and share meanings relevant to the problem-solving task at hand" (Teasley and Roschelle, 1993, p. 229). Research in this area examines methods to accurately capture and analyze student interactions in collaborative or distance learning environments; for example, Soller (2004) described various techniques (e.g., probabilistic machine learning) for modeling knowledge sharing interactions among different learners.

TABLE 24.2
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, learning objects, tasks, items, and/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, review, visualization of goal and/or solution structure)

Simulation and Immersive Environment

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

As we have just shown, many different programs and devices are available to capture, analyze, select, or present information to a learner based on current or perceived needs or 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 literature review on adaptive technologies, we asked leading adaptive-technology experts to address two questions: (1) *what to adapt* (i.e., what variables should be taken into account when implementing an adaptive system?), and (2) *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: (1) input data or *learner variables* to be measured and used as the basis for adaptation, and (2) output or *instructional variables* that adapt to learners' needs and occasionally to preferences. Table 24.2 summarizes their collective responses and illustrates a wide range of student variables and adaptive pedagogical responses.

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 24.3 lists the methods suggested by our experts which represent innovative implementations of the adaptive technologies discussed in Section 24.2.

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 learner model, 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, as well as distributed and collaborative learner modeling in the future. Challenges and envisioned futures are discussed next.

CHALLENGES AND FUTURE OF ADAPTIVE TECHNOLOGIES

Several major obstacles must be overcome for the area of adaptive technologies to move forward. As in the previous section, we have augmented this section by

TABLE 24.3
How To Adapt

Adaptive Approach	Rationale	Refs.
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 action outcomes and combines it with a formal representation of system objectives to identify optimal actions.	Conati (2006)
Constraint-based tutoring	The domain model is represented as a set of constraints on correct solutions; the long-term student model contains constraint histories, and these can be used to generate the system's estimate of students' knowledge. Constraint histories can also be used to generate a population student model (e.g., probabilistic model), which can later be adapted with the student's data to provide adaptive actions (e.g., problem or feedback selection).	Mitrovic (2006)
Concept mapping	Content (e.g., sequences of concepts, learning objects, hints) is adapted to the student by employing a concept map with prerequisite relationships, an overlay model of the students' knowledge, and a reactive planning algorithm.	Vassileva (2006)
Unsupervised machine learning	Most existing student models 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 it may be even impossible because the necessary knowledge does not exist. An alternative is to use unsupervised machine learning to build student models from unlabeled data using clustering techniques for defining classes of user behaviors during learning environment interactions.	Conati (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) learner models in a content management system. Content recommendations to students are based on the learner model, and recommendation is done in a lightweight manner with minimal demands on content developers.	Greer and Brooks (2006)
Analyzing expert teachers	Studying expert teachers/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 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 (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 a couple of experimental studies. 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.	Arroyo et al. (2004, 2006), Woolf (2006)

directly asking leading researchers in the field of adaptive technologies to summarize their views on challenges and the future of adaptive technologies. Our experts include 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 Learner Models

A core challenge of developing effective adaptive technologies is building useful LMs. According to Judy Kay (Kay, 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. As a consequence, 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, 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, when additional interactions are required during the learning process (e.g., completing online questionnaires), this increases the time imposition and can lead to frustration (Kay, 2006) as well as potentially invalid data from students simply trying to get

to the content quickly (Greer and Brooks, 2006). Gathering such information, however, can not only reduce the complexity of diagnosis but also encourage students to become more active participants in learning and 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 (2006b), addressing this problem should begin with the identification of specific conditions that warrant adaptation. There are at least two standards of comparison for adaptivity: (1) fixed sequencing, and (2) learner control of content. The question is whether these comparison conditions accomplish the same goals that could be achieved via adaptation. Jameson (2006b) offers a strategy for finding appropriate adaptivity applications—look for cases where the learner is in a poor position to select content herself, such as: (1) the learner wants to choose an item from a very large set of items whose properties the learner is not familiar with, and (2) the learner is in a situation lacking in the 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 (Fink and Kobsa, 2000; Jameson, 2006b). Another cost-minimizing option has been suggested by Greer and Brooks (2006) that involves leveraging existing content. They note that adaptive algorithms are often domain specific, requiring the hand coding of content to fit the specific form of adaptation. But, 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. Their 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 may then 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. One strategy that addresses this desire is to allow them partial control of the process. According to Jameson (2006b), there are several ways to divide the job of making a learning-path decision by the system vs. the learner (see Wickens and Hollands, 2000, chap. 13). The system can (1) recommend several possibilities and allow the learner to choose from that list; (2) ask the learner for approval of a suggested action; or (3) 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, 2006a). 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 (2006), one way to address this concern is to build all parts of the learner modeling system in a transparent manner to ensure that the learner can scrutinize the system's management of their data and the way in which those data are interpreted (Cook and Kay, 1994).

Considering the Scope of the Learner Model

According to McCalla (2006), adapting to individual differences is essential to making adaptive systems more effective. Despite some support for this claim (Arroyo et al., 2004, 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 use those data as the basis for adapting content (Greer and McCalla, 1994). One major problem concerns obtaining sufficient bandwidth of learner interactions to allow the capture of a sufficient 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, but the good news is that the bandwidth problem is diminishing as learners are currently spending more time interacting with technology (McCalla, 2006), and it is possible to gather a broad range of information about them. Moreover, learners' interactions can now 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, through the eyes of our three experts.

The Future of Adaptive Technology

Judy Kay's Views

A long-term vision for adaptive technologies involves the design and development of life-long learner models 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 life-long LMs 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, as well as its use and reuse. An important part of addressing these issues will be to build LMs and associated applications so learners can always access and control their LMs and their use. This approach must go beyond just making the LM more open and inspectable to ensuring that learners actually take control of its use.

Gord McCalla's Views

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 may also include: (1) artificial agents representing learning objects, and (2) personal agents representing users (e.g., learners, tutors, and teachers). In this vision, each agent maintains models of other agents and users that help the agent 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 the 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* (McCalla et al., 2000).

After a learner has interacted with a learning object, a copy of the model that her 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 must continuously accumulate information, and there can be natural selection as to which objects are useful or not. Useless objects and agents can thus be pruned. Moreover, ecological niches may exist that are based on goals (e.g., certain agents and learning objects are useful for a given goal while 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 (e.g., experimentation to discover algorithms that work for particular kinds of pedagogical goals).

Anthony Jameson's Views

Although there are many improvements that 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 clearly identify 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 have been, and 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 depending on factors such as the emergence of new technologies, new media, advances in learning, measurement, and 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, 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?

Conati (2006) asserts and we agree that *learners' traits targeted for adaptation should clearly improve the pedagogical effectiveness of the system*. This depends on whether or not: (1) a given trait is relevant to achieve the system's pedagogical goals; (2) there is enough learner variability on the trait to justify the need for individualized interaction; and (3) there is sufficient knowledge on how to adapt to learner differences along this trait. Along the same lines, Jameson (2006b) argues 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 and Regian, 1993, p. 268). Evaluation is not only important to the future of the field but can also be as exciting as the process of developing the tools and systems. And, although the results may be surprising or humbling, they will always be informative.

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* Indicates a core reference.