Part I

ADAPTIVE TRAINING TECHNOLOGY

CHAPTER 1

Adaptive Educational Systems

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Introduction

Adaptive educational systems monitor important learner characteristics and make appropriate adjustments to the instructional milieu to support and enhance learning. The goal of adaptive educational systems, 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 & Lee, 2004; Shute et al., 2000; Snow, 1989, 1994).

We present a general evidence-based framework for analyzing adaptive learning technologies. We then describe experts' thoughts on: (1) the variables to be taken into account when implementing an adaptive learning 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 learning technologies. These 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.

Rationale for Adapting Content

The attractiveness of adaptive technologies derives from the wide range of capabilities that these technologies afford. 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, 2007). Many have argued that incoming knowledge is the *single* most important determinant of subsequent learning (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. This 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 & Chen, 2001). For example, training on a foreign language may contain different content depending on whether the learner is a child or an adult.

Differences in Affective Variables

In addition to cognitive, physical, and sociocultural differences, students' affective states fluctuate both within and across individuals. Some of these states – such as frustration, boredom, motivation, and confidence – may influence learning (Conati, 2002; Craig et al., 2004; D'Mello & Graesser, Chapter 6 in this volume; Ekman, 2003; Kapoor & Picard, 2002; Litman & Forbes-Riley, 2004; Picard, 1997; Qu et al., 2005).

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 evidence-based, 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, and metacognitive support. 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 (LM) (see Figure 1.1).[1] The components

[1] The terms "student model" and "learner model" are used interchangeably in this chapter. They are abbreviated 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.

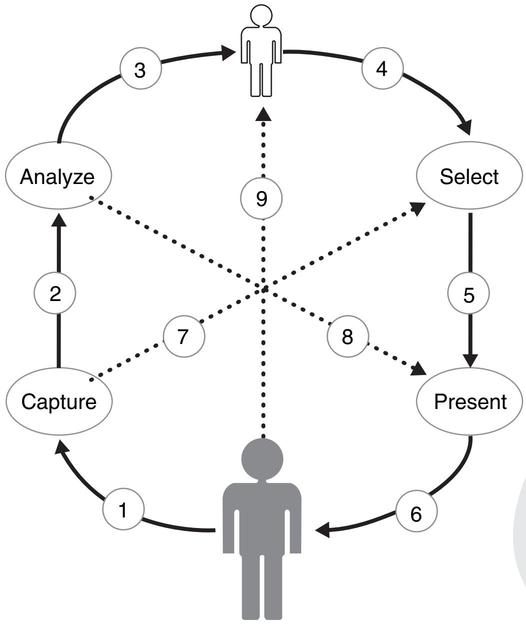

Figure 1.1. Four-process adaptive cycle. The larger human icon represents the student. The smaller human icon represents the student model.

Source: From "Adaptive technologies," by V. J. Shute and D. Zapata-Rivera, 2007, in J. M. Spector, D. Merrill, J. van Merriënboer, & M. Driscoll (Eds.), *Handbook of research on educational communications and technology* (3rd Ed.) (pp. 277–294). New York: Lawrence Erlbaum Associates, Taylor & Francis Group. Copyright © 2007 by the Taylor & Francis Group; reprinted by permission of the publisher.

of this four-process cycle include capture, analyze, select, and present.

CAPTURE

This process entails gathering information about the learner as the learner interacts with the environment (depicted in Figure 1.1 by the larger human figure). Relevant information can include cognitive data (e.g., solution to a given problem) as well as noncognitive aspects of the learner (e.g., engagement). 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. That is, the computer can infer what the learner knows or can do directly from aspects of the learner's performance in the learning domain (e.g., if the learner solves a relatively difficult problem correctly, the inference is that his/her knowledge and/or skill related to the topic is likely pretty good, and if he/she solves another difficult problem correctly, the confidence in the inference that he/she knows the content well increases). In Figure 1.1, this is depicted as the smaller human figure and is often referred to as the student model or the LM.

SELECT

Information (i.e., content in the broadest sense) is selected for a particular learner according to: (1) his/her current status as represented in the student model and (2) the purpose(s) 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 media, devices, and technologies to efficiently convey information to the learner.

This model accommodates alternative types and levels of adaptation. Table 1.1 describes some of the different possibilities, starting with a completely adaptive cycle and continuing to a nonadaptive presentation.

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 & Kobsa, 2000); (2) distributed agent-based platforms (Azambuja et al., 2002; Vassileva et al., 2003); (3) hybrid approaches

Table 1.1. Scenarios Represented in the Four-Process Adaptive Cycle

Scenario	Description
A complete outer cycle, automated adaptation (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 learner model, 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.
Automated adaptation with user input (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 (e.g., overwriting the value of a particular variable). Allowing student input to the model may help reduce the complexity of the diagnostic and selection processes by decreasing the level of uncertainty inherent in the processes. It can also benefit the learner by increasing learner awareness and supporting self-reflection.
Diagnosis only (1, 2, and 3)	The learner is continuously monitored; information gathered is analyzed and used to update learner profiles, but not to adapt content. This may be seen as analogous to student assessment.
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). 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.

involving distributed agents and a student modeling server (Brusilovsky et al., 2005; Zapata-Rivera & Greer, 2004); (4) peer-to-peer architectures (Bretzke & Vassileva, 2003); and (5) service-oriented architectures (Fröschl, 2005; González et al., 2005; Kabassi & Virvou, 2003; Trella et al., 2005; Winter et al., 2005).

To illustrate how our four-process adaptive model can accommodate more distributed scenarios, Figure 1.2 depicts an extended version of our model. Agents (e.g., application, personal, and pedagogical agents) maintain a personal view of the learner using their own representation of the "four-process adaptive cycle" (see Figure 1.1). Agents share (or negotiate) personal information with other agents to accomplish goals on behalf of the learner. A common LM is maintained in a learner modeling server. The term "common learner model" refers to a subset of the LM that is common to all the agents (e.g., identification information) and other information the agents share (e.g., long-term goals and interests).

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; this distinction may be likened to *program* versus *device* 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 LM in its formulation. Also, this listing is intended to be illustrative and not

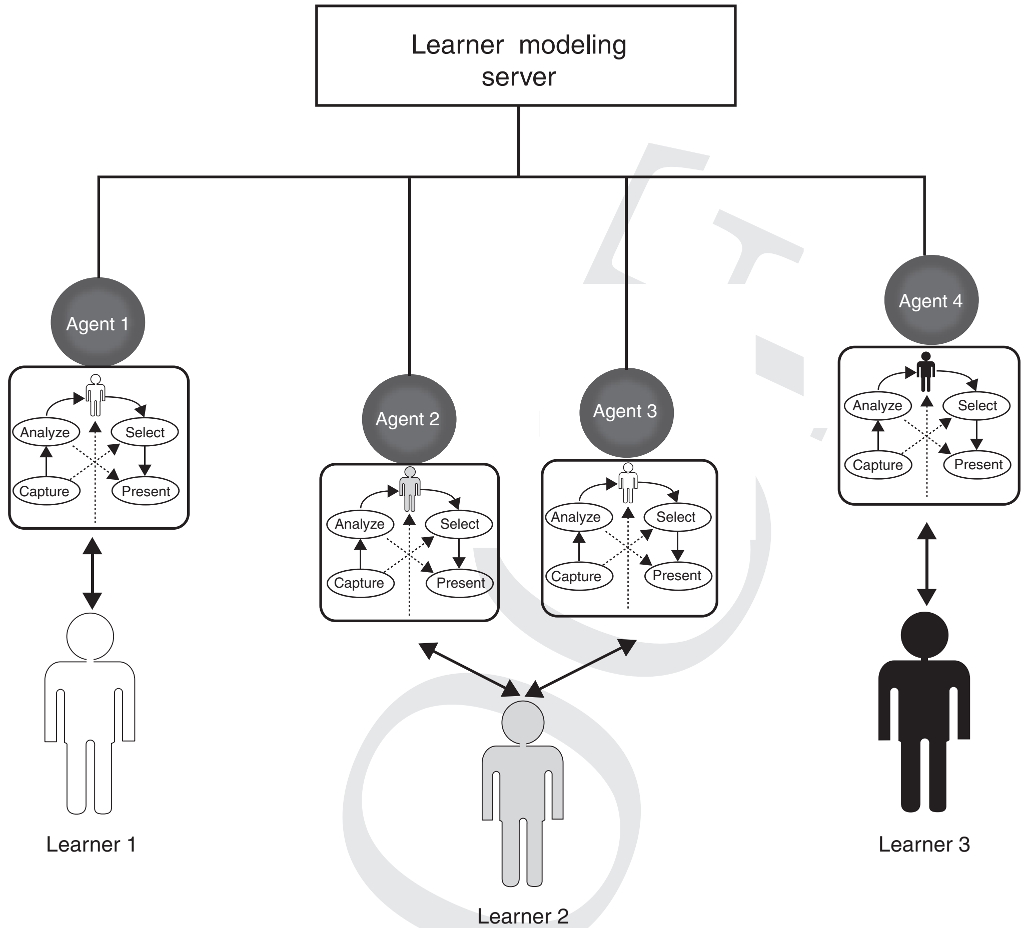

Figure 1.2. Communication among agents and learners.

Source: From "Adaptive technologies," by V. J. Shute and D. Zapata-Rivera, 2007, in J. M. Spector, D. Merrill, J. van Merriënboer, & M. Driscoll (Eds.), *Handbook of research on educational communications and technology* (3rd Ed.) (pp. 277–294). New York: Lawrence Erlbaum Associates, Taylor & Francis Group. Copyright © 2007 by the Taylor & Francis Group; reprinted by permission of the publisher.

exhaustive. For a more thorough description of adaptive technologies in the context of e-learning systems, see Buxton (2006), Fröschl (2005), Jameson (2008), and Kobsa (2006), the first of these for a directory of sources for input technologies.

Figure 1.3 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).

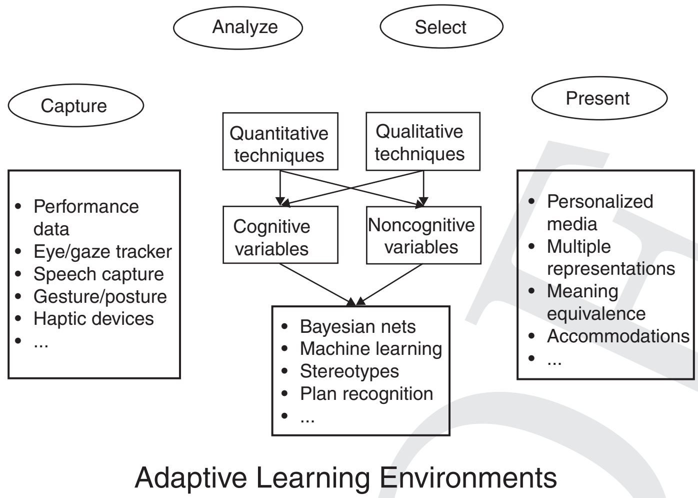

Figure 1.3. Overview of technologies to support learner modeling

Source: From "Adaptive technologies," by V. J. Shute and D. Zapata-Rivera, 2007, in J. M. Spector, D. Merrill, J. van Merriënboer, & M. Driscoll (Eds.), *Handbook of research on educational communications and technology* (3rd Edition) (pp. 277–294). New York: Lawrence Erlbaum Associates, Taylor & Francis Group. Copyright © 2007 by the Taylor & Francis Group; adapted by permission of the publisher.

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 & White, 2002; Leelawong et al., 2001).

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 examples of cognitive models come from the cognitive tutoring research by John Anderson and colleagues (Anderson, 1993; Anderson & Lebiere, 1998; Anderson et al., 1990, 1995; Koedinger & 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. An LM 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 et al. (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 are graphs composed of nodes and directional arrows (Pearl, 1988). Nodes represent variables, and directed edges (arrows) between pairs of nodes indicate probabilistic relationships between variables (Pearl, 1988). Bayesian networks are related to the machine-learning methods (see preceding subsection) 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 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, Hansen, and Almond (2008), 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 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 information 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. The weights represent the probability of a student knowing a particular concept or having a misconception. One of the first uses of an overlay model was done with the WUSOR program (Stansfield et al., 1976). More recent applications of this overlay approach can be found in a variety of research projects (e.g., Kay, 1999; Vassileva, 1998; Zapata-Rivera & Greer, 2000).

PLAN RECOGNITION

A plan is a sequence of actions (which may include choice points) to achieve a certain goal, thus reflecting the learner's intentions and desires. Plan recognition is based on observing the learner's input actions and the system, and 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 (1996).

CUMULATIVE/PERSISTENT STUDENT MODEL

The cumulative student model represents the more traditional approach where the LM 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 are dependent on individual response histories (Shute & Psotka, 1996; VanLehn et al., 2005; Wenger, 1987). Student models can last for a long time and provide valuable information for various applications that keep track of long-term goals and interests. Some researchers have explored these ideas in the context of lifelong user models (e.g., Kay & Kummerfeld, Chapter 7 in this volume).

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 kind of student model is always up to date and corresponds to the short memory cycle scenario shown in Table 1.1.

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 output (presentation).

BIOLOGICALLY BASED DEVICES

So-called biologically based devices obtain physical measures of the student's body or physical activity. They 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. 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 occur 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. The devices can also analyze speech profiles and obtain information on other aspects of the person, such as stress. 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). See also D'Mello and Graesser, Chapter 6 in this volume, and Litman, Chapter 13 in this volume.

HEAD-GESTURE CAPTURE DEVICES

Many computers are currently 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 thirteen 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 (e.g., Kanade, Cohn, & Tian, 2000). This information is used to facilitate human-agent interaction (Cassell et al., 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 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 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; Chapter 3 in this volume). 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 & 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, an LM, observations, and an adaptation component that recommends content and changes the appearance of links and icons. 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 & 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 example, Soller (2004) described various techniques (e.g., probabilistic machine learning) for modeling knowledge-sharing interactions among different learners.

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 an LM (Rickel & Johnson, 1997). Smithtown (Shute & 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 LMs: 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 1.2 summarizes their collective responses and illustrates a wide range of student variables and adaptive pedagogical responses.

Table 1.2. What to Adapt

Variables	Examples
Learner Variables	
Cognitive abilities	Math skills, reading skills, cognitive development stage, problem solving, analogical reasoning.
Metacognitive skills	Self-explanation, self-assessment, reflection, planning.
Affective states	Motivated, attentive, engaged, frustrated.
Additional variables	Personality traits, learner styles, social skills, perceptual skills.
Instructional Variables	
Feedback	Types: hints, explanations. Timing: immediate, delayed.
Content sequencing	Concepts, learning objects, tasks, items, cases or problems to solve.
Scaffolding	Support and fading as warranted; rewards.
View of material	Overview, preview, review, as well as visualization of goal and/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 1.3 lists the methods suggested by our experts, which represent innovative implementations of the adaptive technologies discussed earlier.

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 (for more, see Baker & Yacef, 2009; Beck & Woolf, 2000). 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

Table 1.3. 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, 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	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, 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 can make use (and reuse) of large quantities of high-quality content. This can be done by extending the Shareable Content Object Reference Model (SCORM) Runtime Environment specification to include user-modeling functionality. This permits content authors to take advantage of (and update) LMs in a content-management system. Content recommendations to students are based on the LM and recommendation is done in a lightweight manner with minimal demands on content developers (Greer & 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 to provide effective pedagogical support. An alternative is to run so-called Wizard of Oz studies to test adaptation strategies defined via pedagogical and/or cognitive theories and/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 (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, 2006).

have augmented 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 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 (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 & 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 (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: (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 (2006) 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 & Kobsa, 2000; Jameson, 2006). Another cost-minimizing option has been suggested by Greer and Brooks (2006), which 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 (see Flynn, Chapter 12 in this volume) 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 (2006), there are several ways to divide the job of making a learning-path decision by the system versus the learner (see Wickens & Hollands, 2000, chapter 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.

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, 2008). 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 & 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 an LM that captures certain characteristics of each learner and then 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 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. These views have been crafted from the answers provided by three experts to our questions.

The Future of Adaptive Technology

JUDY KAY'S VIEWS

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 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 his or 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 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 (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 (2006) 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 & 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.

Acknowledgments

We gratefully acknowledge the experts cited herein who provided us with thoughtful and insightful responses to our adaptive-technology queries: Chris Brooks, Cristina Conati, Jim Greer, Anthony Jameson, Judy Kay, Gord McCalla, Tanja Mitrovic, Julita Vassileva, and Beverly Woolf. We also thank Paula J. Durlach and Alan M. Lesgold for their very sage comments on an earlier draft of this chapter.

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