CHAPTER 4 –Matching Learner Models to Instructional Strategies

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Introduction

Learner models represent key variables that guide instructional strategies during e-Learning. By representing key variables about a particular student, learner models make adaptive instruction possible. Without learner models, instruction cannot be individualized and instead is often calibrated to the average ability learner or the lowest ability learner. Learner models enable instruction to focus on what the student doesn't know and adjust to the student's abilities, motivation, and preferences. In other words, learner models enable adaptive instructional strategies.

Given the tight correspondence between learner models and instructional strategies, they must be considered in parallel when designing e-Learning systems. In fact, a strong argument could be made that the choice of instructional strategy drives all other modeling decisions in e-Learning by placing requirements on the learner model and other related models (see Pavlik et al., Chapter 5 in this volume, for a review). Thus, one approach to studying learner models would be to conduct an analysis of all possible instructional strategies and then examine what requirements they place on learner models. However, the vast number of instructional strategies that have been proposed in the literature make this approach somewhat impractical.

In this chapter, we explore an alternative approach to strategy-based analysis of learner models. The Institute for Simulation and Training at the University of Central Florida has recently published an online database known as the Instructional Strategies Indicator (ISI) (Tarr, 2012). The ISI contains 150 instructional strategies, indexed by when and where instruction occurs, the evidence for instructional efficacy, the size of the group being instructed, the expertise of the learner, and the type of knowledge being taught. The ISI represents an effort to organize the known instructional strategies into a comprehensive framework, allowing for the optimal selection of an instructional strategy in a given instructional setting.

The methodology used to create the ISI was qualitative and data-driven, using aspects of grounded theory methodology to select relevant literature and create an analytic framework to describe the literature. Vogel-Walcutt, Fiorella, and Malone (2012) conducted searches of PsychInfo, the Educational Resource Information Center (ERIC), and Google Scholar using a predefined set of search terms and restricting the dates of studies to between 2000 and 2010. Of the 4,515 articles returned, only 771 were retained as relevant to the ISI criteria, which included relevance to military training. In addition to being coded according to the dimensions mentioned above (e.g., when and where instruction occurs), instructional strategies in the retained articles were rated by judges on their associated evidence for efficacy. Strategies were ranked on a 0–9 scale based on multiple criteria of evidence, including empirical results and quality of study, with judges' ratings being checked for inter-rater reliability (Vogel-Walcutt, Malone & Fiorella, 2012). This process yielded 150 different instructional strategies that were included in the ISI. However, only 13 of these strategies were given the highest rating of 7–9, which was reserved for strategies backed by multiple randomized experiments with moderate to large effect sizes ($d \geq 0.5$; Cohen, 1992).

Table 1 presents these 13 strategies with a subset of the ISI dimensions. Missing dimensions include hierarchical categorizations of the strategy type and the knowledge, skills, and abilities to be learned. Included dimensions are (1) timing of instruction relative to the instructional event (pre/during/post), (2) setting of instruction (e.g., computer-based, classroom, or live-training), (3) group size (e.g., individual, small group, or large group), (4) learner's level of expertise (novice/journeyman/expert), (5) knowledge type targeted (declarative/procedural/conceptual/integrated), and (6) rating of evidence for efficacy. Each of these dimensions has previously been described in detail (Vogel-Walcutt, Fiorella & Malone, 2012), but it is outside the scope of this chapter to evaluate the ISI framework or methodology. For the present purposes, it is important to note that the ISI represents a serious attempt to frame the landscape of instructional strategies, and as such it has implications for the study of learner models. The purpose of this chapter is to consider the alignment of learner models to the instructional strategies in Table 4-1.

Table 4-1. Top 13 instructional strategies from the ISI

Name	Time	Setting	Group Size	Level	Knowledge	Rating
Goal Setting	Pre	Any	Individual	Novice	Declarative	7
Scaffolding	During	Any	Individual	Novice	Declarative	8
Distributed Practice	During	Any	Individual	Novice	Declarative	8
Massed Practice	During	Any	Individual	Novice	Procedural	8
Adaptive Instruction	During	Classroom	Individual	Novice	Conceptual	8
Multimedia Instruction	During	Computer-based	Individual	Novice	Conceptual	8
Intelligent Tutoring Systems (ITS)	During	Computer-based	Individual	Novice	Integrated	8
Affective ITS	During	Computer-based	Individual	Journeyman	Conceptual	7
Bayesian Approach	During	Computer-based	Individual	Novice	Conceptual	7
Peer Learning	During	Classroom	Large group	Novice	Conceptual	7
Pedagogical Agent	During	Computer-based	Individual	Novice	Integrative	7
Self Reflection	Post	Classroom	Individual	Novice	Conceptual	7
Self Assessment	Post	Classroom	Individual	Journeyman	Integrative	7

However, even a quick inspection of Table 4-1 reveals that these "strategies" are not equally comparable. Adaptive Instruction is properly viewed as a category that includes ITS, affective ITS, Scaffolding, and the Bayesian Approach, so it arguably could be excluded from further discussion. Likewise, ITSs are a vehicle for delivering strategies; there is no a priori strategy associated with ITSs, except that they are somehow individually adaptive. Finally, the Bayesian Approach is a specific modeling formalism, not a strategy. Although some of the others are not well-defined "strategies" in a strong sense, they are identifiable with strategies, such as Multimedia Instruction (optimal mode of presentation), Pedagogical Agent (social enhancement of learning), and Affective ITS (learning enhancing affect). Therefore, only the following ten strategies will be considered with respect to learner models in the remainder of this chapter. These ten strategies form three natural groupings of self-regulated learning strategies (Goal

Setting, Self-Assessment, and Self-Reflection), social constructivist strategies (Scaffolding, Affective ITS, Peer Learning, and Pedagogical Agent), and memory-enhancing presentation strategies (Distributed Practice, Massed Practice, and Multimedia Instruction). We discuss each of these in turn.

Self-Regulated Learning Strategies

Three of the above ISI strategies are aligned with the four phases of self-regulation: planning/goal setting, monitoring, control, and reflection (Pintrich, 2000). As we proceed, it is important to note that, in a tutor-student or teacher-classroom context, these four phases may be enacted in a distributed way. For example, while the student may have set the initial learning goals, the tutor may be monitoring the student's progress and controlling strategies to facilitate the student's progress. E-learning environments likewise have the same potential to distribute and scaffold self-regulation strategies.

The four phases of self-regulation may manifest in several ways. At any point during the learning session, learners may set goals for learning or goals for performance. During the learning session, learners may monitor their progress toward goals (e.g., judgments of learning or number of pages read). Depending on perceived progress towards goals, learners may invoke a number of control strategies (e.g., paraphrasing, summarizing, note-taking). Finally, learners may reflect on their performance in a more holistic sense and make corresponding attributions (e.g., the material is difficult so this took a long time). Although the four phases above were described from a cognitive viewpoint, the same phases can be applied to self-regulation of motivation/affect, behavior, and learning context (Pintrich, 2000). The following sections describe these four phases in more detail along with the learner model variables needed to support them.

Goal Setting

Reviews of goal setting have found that the specificity, proximity, and difficulty level of goals influence the effects of goal setting (Schunk, 1990; Locke & Latham, 2002). Expended effort increases linearly with task difficulty until the limits of ability are reached. Moreover, specific and difficult goals lead to higher performance than general goals like "Do your best." While general goals reference no objective criterion and so may be ambiguous, specific goals allow a better determination of the required effort and whether success has been achieved. Proximal goals likewise lead to better performance, because progress towards proximal goals is easier to determine than it is for distal goals.

Four mechanisms have been identified that explain the effect of goals on performance (Locke & Latham, 2002). First, goals focus attention of goal-relevant activities. This can help learners ignore information that is irrelevant to the goal. Second, goals activate relevant schemas and procedures for attaining the goal. In cases where the task is familiar, planning and execution will be largely automatic. Third, as mentioned above, level of effort is directly proportional to perceived difficulty. Therefore, more difficult goals can lead to greater effort expended. Fourth, in tandem with increased effort, difficult goals tend to increase the amount of time spent on a task. Given these basic mechanisms involved with goal setting, it makes sense to design instruction so that the performance of the learner is maximized. A fuller description of variables that interact with these mechanisms is reviewed by Locke and Latham (2002).

With these basic principles in mind, it is straightforward to outline some capabilities for a learner model that supports goal setting. First, the learner model should support setting goals before the session that are specific, difficult, and proximal. Thus, ideally, the learner model should not just be used to store arbitrary goals in memory, but should also be used to assess these goals with respect to the student's ability level and the nature of the domain. To prevent goals that are vague, too easy/too difficult for the student, or too distant for the learning session, the learner model should support both evaluation of goals and adaptive guidance to give students feedback on goals. For example, if the goal is too vague, the system might say, "That seems a little vague. How about a more specific goal?" or if the goal is too difficult, the system might say, "That's a good long-term goal, but why don't you simplify it to make it achievable in the amount of time you have?" Of course, assessment of the dimensions of specificity, difficulty, and proximity require complementary modeling of the domain, and the specific feedback offered requires complementary pedagogical modeling (though of a relatively limited sort). Furthermore, if the learner model contains longitudinal information about the student and their previous goals, this information could also be applied to the current situation. For example, if the current situation were similar to a previous situation, the system could remind the user of the associated goal from that previous situation.

Self-Assessment

Self-assessment, by which some criterion (e.g., a goal) is used as a reference to determine progress, is central to monitoring in self-regulated learning. Criteria range from task-specific, as discussed above, to general goal orientations (e.g., mastery and performance goals) (Pintrich, 2000). Externally supplied feedback that link progress towards goals to student strategy use has been found in multiple studies to promote skill and self-efficacy, both when the product of learning and the process of learning are emphasized (Schunk, 1990). Self-assessments may also supply feedback by evaluating level of understanding, personal interests, effort, strategies, history of improvement, and perceived strengths and weaknesses, while fostering students' sense of control over their learning (Paris & Paris, 2001). In a review of the principles of self-assessment, Paris and Winograd (1999) identify three ways in which self-assessment can improve learning. First, awareness of different ways of learning increases when the learning styles and strategies of others are compared to those of the self. Second, efficient allocation of attention and effort requires identifying weaknesses and gaps in knowledge. Finally, self-assessment promotes a sense of self-efficacy and control by promoting effective monitoring and use of repair strategies.

A learner model for self-assessment should incorporate both task-specific and general goal orientations. Task-specific self-assessment is clearly yoked to task goals, as discussed above for goal setting. Thus, task-specific self-assessment involves periodic judgments of progress, effort, effectiveness of employed strategies, and perceived strengths and weakness with regards to specific, proximal, and appropriately difficult goals. How best to represent these quantities is an open question. While some are easily considered as quantities on an ordinal scale (e.g., progress, effort, and effectiveness), in order for a learner model to be highly useful, it should support specific guidance and scaffolding of self-assessment. For example, if the learner notes that some strategies being employed are not effective, the system should be able to comment on the applicability of that strategy in the current context and suggest alternative strategies if appropriate. Such specific remediation is necessary to handle situations where the learner is using the correct strategy in name but is applying the strategy incorrectly. Thus, the learner model should be able to infer strategy use from learner behavior or be able to use self-report (e.g., natural language input) to identify what strategies have been used by the learner.

Self-Reflection

Self-reflection may be considered in terms of the more general goal orientations described above, such as personal interests, history of improvement, and strengths and weaknesses in a less specific and distal context. According to Zimmerman (2002), self-reflection occurs after the learning task but may involve comparisons between self-performance and performance of others or some other standard. These comparisons imply both a backward-looking judgment (at overall performance) and a forward-looking judgment (what performance remains to be achieved). Although arguably these judgments could take place during the learning task, self-reflection also includes attributions that explain overall performance and thus may be considered distinct from self-assessment (Pintrich, 2000; Zimmerman, 2002).

Attributions are causal beliefs about performance that explain performance based on factors that are either outside or within the learner's control. For example, the attribution, "I failed because I'm a stupid person" is a maladaptive attribution because it implies that change is not within the learner's control. Alternatively, adaptive attributions cast failure in terms of specific decisions, like improper strategy use. As reviewed by (Pintrich, 2000), adaptive attributions have been found to increase deeper cognitive processing and improve motivation, affect, and effort.

The general goal orientations involved in self-reflection require tracking learners over longer periods of time. Relevant variables include personal interests, history of improvement, and strengths and weaknesses in a less specific and distal context. The temporal scale of self-reflection suggests that the variables in question will change very slowly. Arguably, self-reflections at this temporal scale are more motivational and affective than cognitive. This implies that a given learner model for general self-reflection can make use of self-report and attempt to update these variables less frequently.

It is important to consider how the learner model of these variables may be used to support motivational or affective functioning. Ideally a system would be able to enhance motivation by presenting the learning task in a way that capitalizes on the learner's interests. When appropriate, the system can use the learner's own sense of personal improvement as a motivational/affective intervention, e.g., "Don't give up now – you were just saying how far you've come." In addition, learner models that track attribution may be important for preventing maladaptive attributions. For example, if the learner articulates a maladaptive attribution during self-reflection, the system would ideally challenge the maladaptive attribution and suggest an alternative explanation.

Table 4-2 summarizes the important variables for learner models.

Table 4-2. Learner model variables for self-regulated strategies

Strategy	Variables
Goal setting	Specificity Difficulty (relative to ability and domain) Proximity
Self-Assessment	Progress Effort Strategy Effectiveness Perceived Strengths and Weakness
Self-Reflection	Personal interests History of improvement Strengths and Weaknesses (Traits)

Social Constructivism

Six of the ISI strategies displayed in Table 4-1 are deeply aligned with learning in a social context. Vygotsky (1978, p. 88) championed the importance of social contexts in the development of learning, writing that "human learning presupposes a specific social nature and a process by which children grow into the intellectual life of those around them." Although just one of the many forms of social constructivism (Palincsar, 1998), Vygotsky's framework is philosophically aligned with many instructional strategies. Perhaps the single most influential idea in Vygotsky's framework is the zone of proximal development, which distinguishes between two levels of ability. The first level describes what children can do on their own. The second level, the zone of proximal development, describes what children can do with the assistance of others. Vygotsky's central claim is that abilities in the zone of proximal development will mature and move into the first level, or in his own words, "What is in the zone of proximal development today will be the actual developmental level tomorrow – that is, what a child can do with assistance today she will be able to do by herself tomorrow" (Vygotsky, 1978, p. 87). The zone of proximal development is consistent with accounts in linguistics and cognitive psychology, which emphasize that "comprehension ... must precede production" (Wood, Bruner & Ross, 1976, p. 90). It is well known that children's comprehension, or receptive capability to comprehend language, precedes their productive capability. Indeed, this is just another way of stating the zone of proximal development – children can comprehend the necessary information with the assistance of others before they can produce it on their own. Instructional strategies inspired by social constructivism and their requisite student models place great emphasis on the adaptive, collaborative, and social nature of learning.

Scaffolding and Affective ITS

The instructional strategy that is perhaps the most aligned with social constructivism is scaffolding. In scaffolding, a student's progress in a learning task is supported by a more experienced other (i.e., person, agent, system) such that scaffolding occurs in the student's zone of proximal development. Scaffolding can be seen clearly in a number of educational interventions in close concert with the instructional strategies of modeling and fading (Collins, Brown & Holum, 1991). In modeling, the instructor demonstrates the learning task, while in scaffolding, the student attempts the task with instructor support. By the time the student has reached fading, the student can engage the task with no (or extremely little) instructor support. This paradigm is also sometimes called "I do, we do, you do." If scaffolding is viewed as a blend of student actions and instructor interventions, then it is clear that it is a continuum with modeling and fading at opposite ends. Therefore, modeling and fading can be considered to be subsumed under scaffolding, representing the two extremes of scaffolded support. An early and profoundly influential study of naturalistic human tutoring describes the scaffolding process in great detail (Wood et al., 1976). According to Wood and colleagues, scaffolding is meant to draw the student into participating in the learning task to the point where the tutor can provide feedback. Over time, the tutor-provided feedback diminishes as the student achieves mastery. A high-level description of the mechanisms required to achieve scaffolding are described as follows:

> *The effective tutor must have at least two theoretical models to which he must attend. One is a theory of the task or problem and how it may be completed. The other is a theory of the performance characteristics of his tutee. Without both of these, he can neither generate feedback nor devise situations in which his feedback will be more appropriate for this tutee in this task at this point in task mastery. The actual pattern of effective instruction, then, will be both task and tutee dependent, the requirements of the tutorial being generated by the interaction of the tutor's two theories.* (Wood et al., 1976, p. 97)

Virtually all known ITSs recognize and embody these two models, generally known as the domain and learner models, which underscores the importance of scaffolding as an instructional strategy. With respect to specific variables in learner models, Wood et al. further specify the processes and mechanisms of scaffolding as consisting of six components:

1. *Recruitment*. The tutor draws the student into the task by gaining their attention, stimulating their interest, and fostering a level of commitment to the learning task.

2. *Reducing degrees of freedom*. The tutor reduces task difficulty to the appropriate level for the student's ability level.

3. *Direction maintenance*. The tutor keeps the student on task by providing affective and motivational support when needed.

4. *Marking critical features*. The tutor provides feedback, hints, and other kinds of guidance that help the student progress in the learning task.

5. *Frustration control*. The tutor prevents negative affect that would impede successful learning.

6. *Demonstration*. The tutor models the learning task based on the student's current attempt, emphasizing the task components where the student is having trouble.

The emphasis on and seamless interweaving of affective and motivational considerations into the above account of a scaffolding is noteworthy. It suggests that scaffolding divorced from these considerations has drifted away from the evidence provided by natural observations of tutoring. We therefore consider what capabilities a learner model should provide to support this entire account of scaffolding, component by component.

Recruitment requires a model of attention such that the presence or absence of a student's attention can be determined. It further requires a notion of student interest in a general sense (i.e., what do students/humans generally find interesting) and/or a notion of a particular student's interests (see *Self-Reflection* above). In either case, a model of interest informs tutor actions that make the connection between student interests and the learning task manifest to the student. Finally, recruitment involves fostering a sense of commitment to the learning task. Commitment may be relative to the student's goals, and so drawing a connection between the learning task and the student's goals provides one approach to fostering commitment (see *Goal Setting* above). However, commitment may also derive from social norms and impulses, such as a desire to please the tutor or otherwise appear competent and knowledgeable. We defer discussion of such matters to the *Pedagogical Agent* section below.

Reducing the degrees of freedom is commonly supported in learner models that assess the ability level of the student and in domain models that represent the difficulty of the material. Ideally, the learner model supports the selection of learning tasks at the appropriate level of difficulty for the student given the student's prior knowledge and progress. Direction maintenance, the third component of scaffolding, entails a model of on- and off-task behavior. Furthermore, the tutor should be able to determine if off-task behavior has resulted from a misunderstanding of the task or if off-task behavior has resulted from negative affective/motivational states leading to an overt abandonment of the learning task or a covert abandonment of the learning task, i.e., "gaming the system" (Baker, Corbett, Koedinger & Wagner, 2004). This distinction should inform whether the tutor uses a cognitive or an affective-oriented strategy to redirect the student to on-task behaviors.

The fourth component, marking critical features, is commonly implemented in learner models that have an overlay model structure (see Pavlik et al., chapter 5 in this volume). Overlay models typically associate mastery scores with elements of the domain model and update these scores based on student progress. Thus, overlay models allow the system to provide feedback to answers as well as hints that suggest what the student should consider next.

Frustration control, the fifth component, again requires a model of learner affect, both in a general sense and in an individualized sense. A general model of frustration includes such variables as affective traits, affective states, and local/global models of task difficulty. Individualized models of frustration may track whether a student has a greater or lesser tendency to become frustrated than the norm (a trait) and with the appropriate sensors even predict frustration in real time at a point in the learning session (a state). Task difficulty models of frustration may include the correlation amongst task difficulty, time on task, and frustration, taking into account that frustration may accumulate over extended periods of task difficulty. Although some analyses of intelligent tutoring systems have found that frustration plays a minor role (Baker, D'Mello, Rodrigo & Graesser, 2010), this could be attributable more to the ability of such systems to maintain appropriate task difficulty rather than to the irrelevance of frustration in learning contexts.

Finally, demonstration (modeling the learning task) requires knowing both when to demonstrate as well as how to demonstrate. Knowing how to demonstrate is a matter decided by the domain model of the learning environment. Knowing when to demonstrate, on the other hand, is an important component of the learner model that relies on tracking the student's ability as well as affective and motivational factors. If the current learning task is judged by the system to be outside the abilities of the student even when hints and feedback are given, then demonstration is warranted both to alleviate this impasse and prevent demotivation and negative affect. An overlay model that accurately assesses the difficulty of the current task, either by comparing it to tasks the student has already mastered or by considering the student's mastery of the component abilities underlying the task compared to other students, may be helpful in determining when demonstration is necessary.

Pedagogical Agent

Pedagogical agents are computer characters who play a social role in a given learning environment. As such, pedagogical agents fit well into the social constructivist perspective. Typically, pedagogical agents are tutor agents, but they may also be peer agents (see *Peer Learning* below). Given the prominence of scaffolding as an instructional strategy, tutor agents are perhaps best considered with regard to the six components of scaffolding considered above. Since humans typically treat computers as social agents and comparably to other humans (Nass, Steuer & Tauber, 1994; Reeves & Nass, 1996; Nass & Moon, 2000), tutor agents have the potential to transparently replace human tutors in computer-based learning environments like intelligent tutoring systems. But if this is the case, one might inquire whether a learning environment, by virtue of running on a computer, is by default imbued with some sort of agency in the mind of the user. If that is the case, then one may ask what pedagogical agents add over and above this default social agency.

A number of additional contributions by pedagogical agents have been described (Johnson, Rickel & Lester, 2000). Central to these contributions is the presentation of the agent as an animated agent, and sometimes as an animated agent in a virtual environment. The first contribution is the ability to present interactive demonstrations, whereby the student can watch the tutor agent demonstrate a motor skill or complex manipulation of an object. Unlike a pre-recorded movie, such a demonstration is potentially parameterizable and could be idealized according to the sixth component of scaffolding mentioned above. The second contribution of animated pedagogical agents (APAs) is the ability to use gaze and gestures to guide student attention (Lester et al., 1999). The ability to direct attention is important in the scaffolding components of recruitment, direction maintenance, and marking critical features. The third contribution, nonverbal feedback, may help with marking critical features. Finally, APAs may convey and elicit emotions, which support the scaffolding components of recruitment, direction maintenance, and frustration control. Given these considerations, it is debatable whether the addition of a pedagogical agent requires changes in the learner model that are not already accounted for by the requirements for scaffolding. If anything, the addition of pedagogical agents may have more implications for the pedagogical model because of the additional capabilities they provide for delivering instructional and affective cues.

It is important to note that APAs have the potential to support scaffolding, but only if they are designed to take advantage of these capabilities. For example, one study that did not take advantage of these capabilities as described above found essentially no differences between three versions of an intelligent tutoring system, namely, animated agent text only, versus synthesized speech only (Graesser et al., 2003). However, a similar study that used a pre-recorded human voice and gestures as the tutor worked through examples found significant learning gains compared to a text-only condition (Atkinson, 2002). Another study manipulated persona to create an emotionless "expert" agent and an emotion-displaying "mentor" agent for two versions of the same learning environment (Baylor & Kim, 2005). That study found that while the expert agent promoted learning gains and was perceived as credible, the mentor agent not only promoted learning gains but also increased self-efficacy. These various studies highlight the potential for APAs to support scaffolding.

Peer Learning

Although peer learning can take many forms, a well-known approach is "reciprocal teaching" (Palincsar & Brown, 1984; Palincsar, 1986). In this program, as instructors read the text, they think aloud to model their comprehension process to the student including their reasoning for when to use each strategy. In a classic modeling-scaffolding-fading paradigm, the instructor and student take turns as the student gradually learns the strategies and practices them while the instructor provides feedback. More specifically, students read paragraph by paragraph and generate questions, summarize, clarify terms and concepts, and make predictions about what is coming up in the text. These practices becomes a dialogue as the instructor comments on and contributes to the student's questions, summaries, and other activities, or as other students make similar contributions in small group sessions. In other words, these activities are situated in an interactive dialogue among instructor and students. In this way, reciprocal teaching creates multiple opportunities for learning: one in the role of the answering student, one in the role of an observing student, and one in the role of the teacher. Each of these roles has a slightly different implication for learner models.

Like tutor agents, peer pedagogical agents may assume social roles in a given learning environment (Kim & Baylor, 2006b), including teachable agent and peer agent. Teachable agents typically have a knowledge representation that human students can directly manipulate (Reif & Scott, 1999; Biswas, Schwartz, Leelawong & Vye, 2005). A well-known teachable agent system is Betty's Brain (Biswas et al., 2005; Leelawong & Biswas, 2008), in which students directly manipulate a concept map (the brain) in order to teach Betty. In Betty's Brain, the domain modeled is typically a causal system in nature, such as ecosystems, the circulatory system, or climate change. Human students use an e-textbook to learn the information to teach Betty. Once a student teaches Betty by building a concept map, Betty can employ qualitative reasoning to reason through a chain of links. This allows Betty to answer questions, take a quiz, or explain her reasoning. Recent experiments indicate that students who teach Betty spend more time on learning tasks compared to students working with the same system but without Betty (Chase, 2011), suggesting that a teachable agent can increase student motivation to learn. The learner model for Betty's Brain mostly centers around the concept map, which is a kind of overlay model on an unseen "expert map," and so learner modeling in this scenario is largely congruent with the typical case in intelligent tutoring systems. However, the special role of human student as teacher can create new opportunities for learner modeling, including teaching-based activities like using the e-book, building the concept map, and taking quizzes. Kinnebrew et al. (2013) explore patterns of student interaction and their implications for student learning. Since the human student can decide what task to perform at any time, they may exhibit learning-promoting behaviors, like careful reading, concept map building, and quiz-taking, or they may exhibit maladaptive behaviors like rapidly alternating between skimming the text, incremental concept map building, and many cycles of quiz failing and re-taking. In systems like Betty's Brain, it becomes even more important to track user interactions to infer what self-regulation strategies (if any) the student is using. These variables are complementary to the self-regulation variables described in Table 4-2.

Peer agents, unlike teachable agents, do not actually learn but instead model behavior to the human student. Peer agents can give answers, express misconceptions, or display affect (Millis et al., 2011). Although multiple dimensions describing peer agents have been proposed (Kim & Baylor, 2006b), perhaps the two most important dimensions are competence and responsiveness. Competency refers to the correctness or quality of the information provided by the peer agent. Responsiveness refers to the initiative the peer agent demonstrates, typically whether it proactively gives advice or not. Note that these dimensions may be applied symmetrically to the human student who is a peer of the agent. A study examining competency and responsiveness found differential effects according to learning outcomes and self-efficacy (Kim & Baylor, 2006a). Students with competent peer agents learned more, but students with less competent peer agents expressed greater self-efficacy. Students with proactive peer agents scored higher on tests of recall than students with low responsive peer agents. While overall these results may suggest that peer agents should be competent and proactive, the study's authors argue that the human student's ability level should be considered when setting the competency or responsiveness of a peer agent. One system combines this suggestion with teachable agents to create a system that enters one of three modes (regular ITS, teachable agent, and vicarious learning) depending on the current ability level of the student (Millis et al., 2011). Significant differences in learning gains in delayed post-test have been found between vicarious and non-vicarious conditions, and it is hypothesized that high ability students should benefit most from teaching agents, and low ability students should benefit most from vicariously observing peer agents model correct behavior.

Table 4-3 summaries important learner variables for the instructional strategies described in this section. Parentheses indicate variables that overlap with previously stated variables in Table 4-2 or that are typically considered part of the domain model.

Table 4-3. Learner model variables for social constructivist strategies

Strategy	Variables
Recruitment	Attention General interest Specific student interest (self-reflection) Commitment (goal setting)
Reducing Degrees of Freedom	Student ability Task difficulty (domain model)
Direction Maintenance	On/off task behavior
Marking Critical Features	Domain model
Frustration Control	Affective traits Affective states Session difficulty (domain model) Task difficulty (domain model)
Demonstration	Task difficulty (domain model) Student ability
Teachable agents	Patterns of interaction to infer strategies
Peer agents	Student ability

Improving Memory

Memory is one of the longest studied topics in the history of psychology (Ebbinghaus, 1913). The range of topics in memory research is immense, ranging from language-based effects to multimedia effects (Byrne, 2008). For the purposes of the present discussion, two topics are particularly relevant, namely, how the temporal structure of practice affects recall and how multimedia presentation affects recall.

Distributed Practice and Massed Practice

The temporal structure of practice is primarily concerned with (1) the duration of study for an item, (2) the temporal interval, or spacing, between repeated presentations of an item, and (3) the retention interval, or time between the last study episode and a retention test (Cepeda, Pashler, Vul, Wixted & Rohrer, 2006). Given these distinctions, massed practice describes practice that emphasizes duration of study of a single item, whereas distributed practice describes practice that emphasizes the spacing between repeated presentations of an item. A recent meta-analysis reports two main finds with respect to distributed and massed practice (Cepeda et al., 2006). First, distributed practice resulted in more correct responses than massed practice for retention intervals ranging from less than 1 min to over a month when study time was held constant. It should be noted that this comparison to "pure" massed practice is unlikely to be consistent with realistic cramming before an exam, which would involve a single session of distributed practice for particular items. Second, for distributed practice, increasing the temporal interval between practices increases accuracy at retention up to a point, but then decreases accuracy after that point, and this optimum spacing increases as the retention interval increases. In other words, for a given retention interval, there is an optimum spacing of practice that maximizes recall. For longer retention intervals, the optimum spacing is longer, and the optimum spacing is shorter for shorter retention intervals. These temporal effects suggest that it is important for learner models to track the presentation history of individual items in order to maximize recall.

Moreover, available research also suggests that individual items can be optimally spaced to maximize the efficiency of learning per unit time (Pavlik & Anderson, 2005, 2008). The basic version of this model, which exhibits good fits to five different human experiments, is based on the declarative memory model of Adaptive Control of Thought-Rational (ACT-R) (Anderson & Lebiere, 1998). Unlike the ACT-R model, which assumes that forgetting is constant, Pavlik and Anderson's basic model assumes that the forgetting rate is a function of the activation of an item. An elaborated version of this basic model considers how to best balance spacing with studying, such that recall is optimized for a given period of study (Pavlik & Anderson, 2008), which we summarize below. This optimization is important because spacing and studying are somewhat at odds. Longer spacing improves long-term recall on retention tests, but short-term is likely to increase forgetting and, by implication, restudying. However, restudying takes time, so a successful recall trial takes less time than an unsuccessful trial that necessitates restudying.

Using the extended ACT-R model, Pavlik and Anderson define a learning rate measure by which they can select the optimal item for practice on any given trial. The learning rate is based on the predicted activation gain for an item at the retention interval, but normalized for the time cost to practice that item. At any given moment, items will have different learning rate values, but one will be closest to its maximum learning rate. Although the items are not explicitly compared with each other to select the optimal item, because the basic model limits the gains of activation for items that are already highly activated, the model has a preference for items with relatively low activation. In experimental comparisons, the optimized schedule of practice was significantly better in terms of recall and latency, with large effect sizes, than a flashcard-based system and another optimized schedule that predicted recall as a function of practice. These findings suggest that both the presentation history of items (correct trials and incorrect+restudy trials for each item) and the time cost to practice any item should be considered to optimize recall. Specific learner model variables include item probability of correctness, response latency, and failure latency.

Multimedia Instruction

Multimedia consists of auditory and visual representations of words and images. Examples of multimedia include illustrated books, television, and computer-based learning environments. According to Mayer (2008), the fundamentals of multimedia learning are that (1) we have dual channels for processing auditory and visual stimuli, (2) we have limited capacity to process information at a given point in time, and (3) we learn deeply by organizing and integrating information during learning. Mayer elaborates these fundamentals in ten principles that together optimize the active processing of information by respecting the limitations of cognitive processing.

We briefly summarize these ten principles, each of which specifies how information should be presented to the learner:

1. Extraneous material should be reduced to the extent possible
2. Essential material should be highlighted by overviewing the main ideas
3. Redundancy in separate channels helps learning, but redundancy in the same channel hurts learning.
4. Spatial contiguity should be preserved, e.g., by placing words next to their respective images.
5. Temporal contiguity should be preserved by synchronizing presentation of related information that is in different channels.
6. Material should be presented in small chunks.
7. Pretraining should be used to basic vocabulary and concepts before attempting to teach a complex system.
8. Spoken text and images should be used instead of printed text and images.
9. Spoken text and pictures should be used instead of either alone.
10. Material should be presented in a personalized conversational style.

The extent to which the principles of multimedia instruction align with learner models is somewhat suspect. These principles state general constraints with regard to human cognition, and so do not represent variables that would be tracked for an individual in order to optimize instruction for that individual. The theory of learning styles has been proposed, by which individuals may vary in how they best learn from different modes of information presentation, but little evidence has been found to support these claims (Pashler et al., 2008). Therefore, multimedia principles may be best applied to the domain or pedagogical models – in the design of the instruction itself.

Table 4-4 summarizes the important learner model variables discussed in this section.

Table 4-4. Learner model variables for improving memory

Strategy	Variables
Practice	Number of trials Delay between trials
Optimal practice	Probability of correctness Response latency Failure latency

Conclusion

In this chapter, we examined the top ten strategies of the ISI from the perspective of learner models. Most of the ten strategies could be associated with concrete variables that a learner model must include in order to support that strategy. This was true for the self-regulated strategies that included variables for proximal and distal goals, personal interests, history of improvement, attributions, and strategy use either through self-report or inference from student behavior. The social-constructivist strategies include the classic learner model variables associated with scaffolding such as overlay models on the domain that specify the difficulty level of material and the student's ability, student interests, affect, goals, and on-off task behavior. Pedagogical agents, while providing potential affective and gestural support for scaffolding, have little correspondence to the learner model except perhaps by virtue of learner preferences. Peer learning has different implications for learner models depending on whether the peer is a teachable agent (with the human student as the teacher) or a collaborative peer. Teachable agents create a context for a host of new variables tracking the strategies and behaviors used by the human student (e.g., quizzing the teachable agent or studying an e-book in preparation of teaching the agent). Use of collaborative peer agents may benefit from learner models that track the ability level and self-efficacy of the human student, but this question awaits future research. Memory-enhancing presentation strategies likewise differ on their learner modeling needs. Distributed practice (which subsumes massed practice in real-world contexts) at the extreme can require extensive item level variables that track the accumulation of practice and the rate of forgetting. Multimedia instruction, in contrast, is guided by a set of principles that are not learner-specific. As a result they are perhaps best situated outside the learner model.

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