

ADAPTIVE INSTRUCTIONAL SYSTEMS

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A central and persisting issue in educational technology is the provision of instructional environments and conditions that can comply with individually different educational goals and learning abilities. Instructional approaches and techniques that are geared to meet the needs of the individually different student are called adaptive instruction (Como & Snow, 1986). More specifically, adaptive instruction refers to educational interventions aimed at effectively accommodating individual differences in students while helping each student develop the knowledge and skills required to learn a task. Adaptive instruction is generally characterized as an educational approach that incorporates alternative procedures and strategies for instruction and resource utilization and has the built-in flexibility to permit students to take various routes to, and amounts of time for, learning (Wang & Lindvall, 1984). Glaser (1977) described three essential ingredients of adaptive instruction. First, it provides a variety of alternatives for learning and many goals from which to choose. Second, it attempts to utilize and develop the capabilities that an individual brings to the alternatives for his or her learning and to adjust to the learner's particular talents, strengths, and weaknesses. Third, it attempts to strengthen an individual's ability to meet the demands of available educational opportunities and develop the skills necessary for success in the complex world.

Adaptive instruction has been used interchangeably with individualized instruction in the literature (Reiser, 1987; Wang & Lindvall, 1984). However, they are different depending on the specific methods and procedures employed during instruction. Any type of instruction presented in a one-on-one setting can

be considered individualized instruction. However, if that instruction is not flexible enough to meet the student's specific learning needs, it cannot be considered adaptive. Similarly, even though instruction is provided in a group environment, it can be adaptive if it is sensitive to the unique needs of each student as well as the common needs of the group. Ideal individualized instruction should be adaptive, because instruction will be most powerful when it is adapted to the unique needs of each individual. It can easily be assumed that the superiority of individualized instruction over group instruction reported in many studies (e.g., Bloom, 1984; Kulik, 1982) is due to the adaptive nature of the individualized instruction.

The long history of thoughts and admonitions about adapting instruction to individual student's needs has been documented by many researchers (e.g., Como & Snow, 1986; Federico, 1980; Reiser, 1987; Tobias, 1989). Since at least the fourth century BC, adapting has been viewed as a primary factor for the success of instruction (Como & Snow, 1986), and adaptive instruction by tutoring was the common method of education until the mid-1800s (Reiser, 1987). Even after graded systems were adopted, the importance of adapting instruction to individual needs was continuously emphasized. For example, Dewey (1902/1964), in his 1902 essay, "Child and Curriculum," deplored the current emphasis on a single kind of curriculum development that produced a uniform, inflexible sequence of instruction that ignored or minimized the child's individual peculiarities, whims, and experiences. Nine years later, Thorndike (1911) argued for a specialization of instruction that acknowledged differences

¹Views and opinions expressed in this chapter are solely the author's and do not represent or imply the views or opinions of the U.S. Department of Education or the Institute of Education Sciences.

among pupils within a single class as well as specialization of the curriculum for different classes. Since then, various approaches and methods have been proposed and attempted to provide adaptive instruction to individually different students (for early systems see Reiser, 1987).

Particularly since Cronbach (1957) declared that a united discipline of psychology not only will be interested in organism and treatment variables but also will be concerned with the otherwise ignored interactions between organism and treatment variables, numerous studies have been conducted to investigate what kinds of student characteristics and background variables should be considered in adapting instruction to individuals and how instructional methods and procedures should be adapted to those characteristics and variables (Cronbach, 1971; Cronbach & Snow, 1977; Federico, 1980; Snow & Swanson, 1992). It is surprising, however, how little scientific evidence has been accumulated for such adaptations and how difficult it is to provide guidelines to practitioners for making such adaptations.

This chapter has four objectives: (a) to review selectively systematic efforts to establish and implement adaptive instruction, including recently developed technology-based systems such as hypermedia and Web-based systems, (b) to discuss theoretical paradigms and research variables studied to provide theoretical bases and development guidelines of adaptive instruction, (c) to discuss problems and limitations of the current approach to adaptive instruction, and (d) to propose a response-sensitive approach to the development of adaptive instruction.

25.1 ADAPTIVE INSTRUCTION: THREE APPROACHES

The efforts to develop and implement adaptive instruction have taken different approaches based on the aspects of instruction that are intended to adapt to different students. The first approach is to adapt instruction on a macrolevel by allowing different alternatives in selecting only a few main components of instruction such as instructional goals, depth of curriculum content, and delivery systems. Most adaptive instructional systems developed as alternatives to the traditional lock-step group instruction in school environments have taken this approach. In this macroapproach, instructional alternatives are selected mostly on the basis of the student's instructional goals, general ability, and achievement levels in the curriculum structure. The second approach is to adapt specific instructional procedures and strategies to specific student characteristics. Because this approach requires the identification of the most relevant learner characteristics (or aptitudes) for the instruction and the selection of instructional strategies that best facilitate the learning process of the students who have the aptitudes, it is called aptitude-treatment interactions (ATI). The third approach is to adapt instruction on a microlevel by diagnosing the student's specific learning needs during instruction and providing instructional prescriptions for the needs. As this microapproach is designed to guide the student's ongoing learning process throughout the instruction, the diagnosis and prescription are often continuously performed from analysis of the student's performance on the task.

The degree of adaptation is determined by how sensitive the diagnostic procedure is to the specific learning needs of each student and how much the prescriptive activities are tailored to the learner's needs. Depending on the available resources and constraints in the given situation, the instruction can be designed to be adaptive using a different combination of the three approaches. However, the student in an ideal microadaptive system is supposed to achieve his or her instructional objective by following the guidance that the system provides. The rapid development of computer technology has provided a powerful tool for developing and implementing microadaptive instructional systems more efficiently than ever before. Thus, in this chapter microadaptive instructional systems and the related issues are reviewed and discussed more thoroughly than macroadaptive systems and ATI approaches. Our review includes adaptive approaches used in recently developed technology-based learning environments such as hypermedia and Web-based instruction. However, the most powerful form of technology-based adaptive systems, intelligent tutoring systems (ITSs), is briefly reviewed on only a conceptual level here because another chapter is devoted to ITSs. Also, learner control, another form of adaptive instruction, is not discussed in depth because it is covered in another chapter.

25.2 MACRO-ADAPTIVE INSTRUCTIONAL SYSTEMS

Early attempts to adapt the instructional process to individual learners in school education were certainly macrolevel because the students were simply grouped or tracked by grades or scores from ability tests. This homogeneous grouping had a minimal effect because the groups seldom received different kinds of instructional treatments (Tennyson, 1975). In the early 1900s, however, a number of adaptive systems were developed to accommodate different student abilities better. For example, Reiser (1987) described the Burke plan, Dalton plan, and Winnetka plan that were developed in the early 1900s. The main adaptive feature in these plans was that the student was allowed to go through the instructional materials at his or her own pace. The notion of mastery learning was also fostered in the Dalton and Winnetka plans (Reiser, 1987).

Since macroadaptive instruction is frequently used within a class to aid the differentiation of teaching operations over larger segments of instruction, it often involves a repeated sequence of "recitation" activity initiated by teachers' behaviors in classrooms (Como & Snow, 1983). For example, a typical pattern of teaching is (a) explaining or presenting specific information, (b) asking questions to monitor student learning, and (c) providing appropriate feedback for the student's responses. Several macroadaptive instructional systems developed in the 1960s are briefly reviewed here.

25.2.1 The Keller Plan

In 1963, Keller (1968, 1974) and his associates at Columbia University developed a macroadaptive system called the Keller plan in which the instructional process was personalized for

each student. The program incorporated four unique features: (a) requiring mastery of each unit before moving to the next unit, (b) allowing a self-learning pace, (c) using textbooks and workbooks as the primary instructional means, and (d) using student proctors for evaluating student performance and providing feedback. The Keller plan was used at many colleges and universities throughout the world (Reiser, 1987) during the late 1960s and early 1970s.

25.2.2 The Audio-Tutorial System

In 1961, the Audio-Tutorial System (Postlethwait, Novak, & Murray, 1972) was developed at Purdue University by applying audiovisual media, particularly audiotape. The unique feature of this audiotutorial approach was a tutorial-like instruction using audiotapes, along with other media such as texts, slides, and models. This approach was effectively used for teaching college science courses (Postlethwait, 1981).

25.2.3 PLAN

In 1967, Flanagan, Shanner, Brudner, and Marker (1975) developed a Program for Learning in Accordance with Needs (PLAN) to provide students with options for selecting different instructional objectives and learning materials. For the selected instructional objective(s), the student needed to study a specific instructional unit and demonstrate mastery before advancing to the next unit for another objective(s). In the early 1970s, more than 100 elementary schools participated in this program.

25.2.4 Mastery Learning Systems

A popular approach to individualized instruction was developed by Bloom and his associates at the University of Chicago (Block, 1980). In this mastery learning system, virtually every student achieves the given instructional objectives by having sufficient instructional time and materials for his or her learning. "Formative" examination is given to determine whether the student needs more time to master the given unit, and "summative" examination is given to determine mastery. The mastery learning approach was widely used in the United States and several foreign countries. The basic notion of mastery learning, initially proposed by Carroll (1963), is still alive at many schools and other educational institutes. However, the instructional adaptiveness of this mastery learning approach is mostly limited to the "time" variable.

25.2.5 IGE

A more comprehensive macro-adaptive instructional system, called Individually Guided Education (IGE), was developed at the University of Wisconsin in 1965 (Klausmeier, 1975, 1976). In IGE, instructional objectives are first determined for each student based on his or her academicability profile, which includes diagnostic assessments in reading and mathematics, previous achievements, and other aptitude and motivation data. Then, to

accommodate different student learning abilities and styles, the teacher determines the necessary guidance for each student and selects alternative instructional materials (e.g., text, audiovisuals, and group activities) and interactions with other students. The goals and implementation methods of this program could be changed to comply with the school's educational assumptions and institutional traditions (Klausmeier, 1977). However, an evaluation study by Popkewitz, Tabachnick, and Wehlage (1982) reported that the implementation and maintenance of IGE in existing school systems were greatly constrained by the school environments.

25.2.6 IPI

The Individually Prescribed Instructional System (IPI) was developed by the Learning Research and Development Center (LRDC) at the University of Pittsburgh in 1964 to provide students with adaptive instructional environments (Glaser, 1977). In the IPI, the student was assigned to an instructional unit within a course according to the student's performance on a placement test given before the instruction. Within the unit, a pretest was given to determine which objectives the student needed to study. Learning materials required to master the instructional objectives were prescribed. After studying each unit, students took a posttest to determine their mastery of the unit. The student was required to master specific objectives for the instructional unit before advancing to the next unit.

25.2.7 ALEM

The LRDC extended the IPI with more varied types of diagnosis methods, remedial activities, and instructional prescriptions. The extended system is called the Adaptive Learning Environments Model (ALEM) (Wang, 1980). The main functions of the ALEM include (a) instructional management for providing learning guidelines on the use of instructional time and resources materials, (b) guidance for parental involvements at home in learning activities provided at school, (c) a procedure for team teaching and group activities, and (d) staff development for training teachers to implement the system (Como & Snow, 1983). An evaluation study (Wang & Walberg, 1983) reported that 96% of teachers were able to establish and maintain the ALEM in teaching economically disadvantaged children (kindergarten through grade 3) and that the degree of its implementation was associated with students' efficient use of learning time and with constructive classroom behaviors and processes.

25.2.8 CMI Systems

Well-designed computer-managed instructional (CMI) systems have functions to diagnose student learning needs and prescribe instructional activities appropriate for the needs. For example, the Plato Learning Management (PLM) System at Control Data Corporation had functions to give a test on different levels of instruction: an instructional module, a lesson, a course, and a curriculum. An instructional module was designed to teach one or more instructional objectives, a lesson consisted of one or

more modules, a course consisted of one or more lessons, and a curriculum had one or more courses. A CMI system can evaluate each student's performance on the test and provide specific instructional prescriptions. For example, if a student's score has not reached the mastery criterion for a specific instructional objective on the module test, it can assign a learning activity or activities for the student. After studying the learning activities, the student may be required to take the test again. When the student demonstrates the mastery of all objectives in the module, the student will be allowed to move on to the next module. Depending on the instructor's or instructional administrator's choice, the student can complete the lesson, course, or curriculum by taking only corresponding module tests, although the student may be required to take additional summary tests on the lesson level, course level, and curriculum level. In either case, this test-evaluation-assignment process is continued until the student demonstrates the mastery of all the objectives, modules, lessons, courses, and curriculum. In addition to the test-evaluation-prescription process, a CMI system may have several other features important in adapting instruction to the student's needs and ability: (a) The instructor can be allowed to choose appropriate objectives, modules, lessons, and courses in the curriculum for each student to study; (b) the student can decide the sequence of instructional activities by choosing a specific module to study; (c) more than one learning activity can be associated with an instructional objective, and the student can have the option to choose which activity or activities to study; and (d) because most learning activities associated with a CMI system will be instructor-free, the student can choose the time to study it and progress at his or her own pace.

As described above, well-designed CMI systems provided many important macro-adaptive instructional features. Although the value of a CMI system was well understood, its actual use was limited due to the need for a central computer system that allowed the instructor to monitor and control the student's learning activities at different locations and different times. However, the dramatic increase in personal computer (PC) capability and the simple procedure to make linkages among PCs made it easy to provide a personalized CMI system.

Ross and Morrison (1988) developed a macroadaptive system combining some of the basic functions of CMI (e.g., prescription of instruction) and some of the features of microadaptive models (e.g., prediction of student learning needs). This system was designed primarily for providing adaptive instruction rather than managing the instructional process. However, the student's learning needs were diagnosed only from preinstructional data, and a new instructional prescription could not be generated until the next unit of instruction began. It consisted of three basic steps: First, variables for predicting the student's performance on the task were selected (e.g., measures of prior knowledge, reading comprehension, locus of control, and anxiety). Second, a predictive equation was developed using multiple regression analysis. Third, an instructional prescription (e.g., necessary number of examples estimated to learn the task) was selected based on the student's predicted performance. This system was developed by simplifying a microadaptive model (trajectory/multiple regression approach) described in a later section.

The macro-adaptive instructional programs just described are representative examples that have been used in existing educational systems. As mentioned at the beginning of this chapter, macro-adaptive instruction, except for CMI systems, has been a common practice in many school classrooms for a long time, although the adaptive procedures have been mostly unsystematic and primitive, with the magnitude of adaptation differing widely among teachers. Thus, several models have been proposed to examine analytically the different levels and methods of adaptive instruction and to provide guidance for developing adaptive instructional programs.

25.3 MACRO-ADAPTIVE INSTRUCTIONAL MODELS

25.3.1 A Taxonomy of Macro-Adaptive Instruction

Como and Snow (1983) developed a taxonomy of adaptive instruction to provide systematic guidance in selecting instructional mediation (i.e., activities) depending on the objectives of adaptive instruction and student aptitudes. Como and Snow distinguished two objectives of adaptive instruction: (a) aptitude development necessary for further instruction such as cognitive skills and strategies useful in later problem solving and effective decision making and (b) circumvention or compensation for existing sources of inaptitude needed to proceed with instruction. They categorized aptitudes related to learning into three types: intellectual abilities and prior achievement, cognitive and learning styles, and academic motivation and related personality characteristics. (For in-depth discussions on aptitudes in relation to adaptive instruction, see Cronbach and Snow [1977], Federico [1980], Snow [1986], Snow and Swanson, [1992], and Tobias [1987].) Como and Snow categorized instructional mediation into four types, from the least to the most intrusive: (a) activating, which mostly calls forth students' capabilities and capitalizes on learner aptitudes as in discovery learning; (b) modeling; (c) participant modeling; and (d) short-circuiting, which requires step-by-step direct instruction. This taxonomy gives a general idea of how to adapt instructional mediation for the given instructional objective and student aptitude. According to Como and Snow (1983), this taxonomy can be applied to both levels of adaptive instruction (macro and micro). For example, the activating mediation may be more beneficial for more intellectually able and motivated students, while the short-circuiting mediation may be better for intellectually low-end students. However, this level of guidance does not provide specific information about how to develop and implement an adaptive instruction. More specifically, it does not suggest how to perform ongoing learning diagnosis and instructional prescriptions during the instructional process.

25.3.2 Macro-Adaptive Instructional Models

Whereas Como and Snow's taxonomy represents possible ranges of adaptation of instructional activities for the given

instructional objective and student aptitudes, Glaser's (1977) five models provide specific alternatives for the design of adaptive instruction. Glaser's first model is an instructional environment that provides limited alternatives. In this model, the instructional objective and activity to achieve the objective are fixed. Thus, if students do not have the appropriate initial competence to achieve the objective with the given activity, they are designated poor learners and are dropped out. Only students who demonstrate the appropriate initial state of competence are allowed to participate in the instructional activity. If students do not demonstrate the achievement of the objective after the activity, they are allowed to repeat the same activity or are dropped out. The second model provides an opportunity to develop the appropriate initial competence for students who do not have it. However, no alternative activities are available. Thus, students who do not achieve the objective after the activity should repeat the same activity or drop out. The third model accommodates different styles of learning. In this model, alternative instructional activities are available, and students are assessed as to whether they have the appropriate initial competence for achieving the objective through one of the alternatives. However, there are no remedial activities for the development of the appropriate initial competence. Thus, if a student does not have initial competence appropriate for any of the alternative activities, he or she is designated a poor learner. Once an instructional activity is selected based on the student's initial competence, the student should repeat the activity until achieving the objective or drop out. The fourth model provides an opportunity to develop the appropriate initial competence and accommodate different styles of learning. If the student does not have the appropriate initial competence to achieve the objective through any of the alternative instructional activities, a remedial instructional activity is provided to develop the initial competence. If the student has developed the competence, an appropriate instructional activity is selected based on the nature of the initial competence. The student should repeat the selected instructional activity until achieving the objective or drop out. The last model allows students to achieve different types of instructional objectives or different levels of the same objective depending on their individual needs or ability. The basic process is the same as the fourth model, except that the student's achievement is considered successful if any of the alternative instructional objectives (e.g., different type or different level of the same objective) are achieved.

Glaser (1977) described six conditions necessary for instantiating adaptive instructional systems: (a) The human and mental resources of the school should be flexibly employed to assist in the adaptive process; (b) curricula should be designed to provide realistic sequencing and multiple options for learning; (c) open display and access to information and instructional materials should be provided; (d) testing and monitoring procedures should be designed to provide information to teachers and students for decision making; (e) emphasis should be placed on developing abilities in children that assist them in guiding their own teaming; and (f) the role of teachers and other school personnel should be the guidance of individual students. Glaser's conditions suggest that the development and implementation of an adaptive instructional program in an existing system are

complex and difficult. This might be the primary reason why most macro-adaptive instructional systems have not been used as successfully and widely as hoped. However, computer technology provides a powerful means to overcome at least some of the problems encountered in the planning and implementing of adaptive instructional systems.

25.4 APTITUDE–TREATMENT INTERACTION MODELS

Cronbach (1957) suggested that facilitating educational development in a wide range of students would require a wide range of environments suited to the optimal learning of the individual student. For example, instructional units covering available content elements in different sequences would be adapted to differences among students. Cronbach's strategy proposed prescribing one type of sequence (and even media) for a student of certain characteristics, and an entirely different form of instruction for another learner of differing characteristics. This strategy has been termed ATI. Cronbach and Snow (1977) defined aptitude as any individual characteristic that increases or impairs the student's probability of success in a given treatment and treatment as variations in the pace or style of instruction. Potential interactions are likely to reside in two main categories of aptitudes for learning (Snow & Swanson, 1992): cognitive aptitudes and conative and affective aptitudes. Cognitive aptitudes include (a) intellectual ability constructs consisting mostly of fluid analytic reasoning ability, visual spatial abilities, crystallized verbal abilities, mathematical abilities, memory space, and mental speed; (b) cognitive and learning styles; and (c) prior knowledge. Conative and affective aptitudes include (a) motivational constructs such as anxiety, achievement motivation, and interests and (b) volitional or action-control constructs such as self-efficacy.

To provide systematic guidelines in selecting instructional strategies for individually different students, Carrier and Jonassen (1988) proposed four types of matches based on Salomon's (1972) work: (a) remedial, for providing supplementary instruction to learners who are deficient in a particular aptitude or characteristic; (b) capitalization/preferential, for providing instruction in a manner that is consistent with a learner's preferred mode of perceiving or reasoning; (c) compensatory, for supplanting some processing requirements of the task for which the learner may have a deficiency; and (d) challenge, for stimulating learners to use and develop new modes of processing.

25.4.1 Aptitude Variables and Instructional Implications

To find linkages between different aptitude variables and learning, numerous studies have been conducted (see Cronbach & Snow, 1977; Gagné, 1967; Gallagher, 1994; Snow, 1986; Snow & Swanson, 1992; Tobias, 1989, 1994). Since the detailed review of ATI research findings is beyond the scope of this chapter, a few representative aptitude variables showing relatively

important implications for adaptive instruction are briefly presented here.

25.4.1.1 Intellectual Ability. General intellectual ability consisting of various types of cognitive abilities (e.g., crystallized intelligence such as verbal ability, fluid intelligence such as deductive and logical reasoning, and visual perception such as spatial relations) (see Snow, 1986) is suggested to have interaction effects with instructional supports. For example, more structured and less complex instruction (e.g., expository method) may be more beneficial for students with low intellectual ability, while less structured and more complex instruction (e.g., discovery method) may be better for students with high intellectual ability (Snow & Lohman, 1984). More specifically, Como and Snow (1986) suggested that crystallized ability may relate to, and benefit in interaction with, familiar and similar instructional methods and content, whereas fluid ability may relate to and benefit from learning under conditions of new or unusual methods or content.

25.4.1.2 Cognitive Styles. Cognitive styles are characteristic modes of perceiving, remembering, thinking, problem solving, and decision making. They do not reflect competence (i.e., ability) per se but, rather, the utilization (i.e., style) of competence (Messick, 1994). Among many dimensions of cognitive style (e.g., field dependence versus field independence, reflectivity versus impulsivity, haptic versus visual, leveling versus sharpening, cognitive complexity versus simplicity, constricted versus flexible control, scanning, breadth of categorization, and tolerance of unrealistic experiences), field-dependent versus field-independent and impulsive versus reflective styles have been considered to be most useful in adapting instruction. The following are instructional implications of these two cognitive styles that have been considered in ATI studies.

Field-independent persons are more likely to be self-motivated and influenced by internal reinforcement and better at analyzing features and dimensions of information and for conceptually restructuring it. In contrast, field-dependent persons are more likely to be concerned with what others think and affected by external reinforcement and accepting of given information as it stands and more attracted to salient cues within a defined learning situation. These comparisons imply some ATI research. For example, studies showing significant interactions revealed that field-independent students achieved best with deductive instruction, and field-dependent students performed best in instruction based on examples (Davis, 1991; Messick, 1994).

Reflective persons are likely to take more time to examine problem situations and make fewer errors in their performance, to exhibit more anxiety over making mistakes on intellectual tasks, and to separate patterns into different features. In contrast, impulsive persons have a tendency to show greater concern about appearing incompetent due to slow responses and take less time examining problem situations and to view the stimulus or information as a single, global unit. As some of the instructional implications described above suggest, these two cognitive styles are not completely independent of each other (Vernon, 1973).

25.4.1.3 Learning Styles. Efforts to match instructional presentation and materials with the student's preferences and needs have produced a number of learning styles (Schmeck, 1988). For example, Pask (1976, 1988) identified two learning styles: holists, who prefer a global task approach, a wide range of attention, reliance on analogies and illustrations, and construction of an overall concept before filling in details; and serialists, who prefer a linear task approach focusing on operational details and sequential procedures. Students who are flexible employ both strategies and are called versatile learners (Messick, 1994). Marton (1988) distinguished between students who are conclusion oriented and take a deep-processing approach to learning and students who are description oriented and take a shallow-processing approach. French (1975) identified seven perception styles (print oriented, aural, oral-interactive, visual, tactile, motor, and olfactory) and five concept formation approaches (sequential, logical, intuitive, spontaneous, and open). Dunn and Dunn (1978) classified learning stimuli into four categories (environmental, emotional, sociological, and physical) and identified several learning styles within each category. The student's preference in environmental stimuli can be quiet or loud sound, bright or dim illumination, cool or warm temperature, and formal or informal design. For emotional stimuli, students may be motivated by self, peer, or adult (parent or teacher), more or less persistent, and more or less responsible. For sociological stimuli, students may prefer learning alone, with peers, with adults, or in a variety of ways. Preferences in physical stimuli can be auditory, visual, or tactile/kinesthetic. Kolb (1971, 1977) identified four learning styles and a desirable learning experience for each style: (a) Feeling or enthusiastic students may benefit more from concrete experiences, (b) watching or imaginative students prefer reflective observations, (c) thinking or logical students are strong in abstract conceptualizations, and (d) doing or practical students like active experimentation. Hagberg and Leider (1978) also developed a model for identifying learning styles, which is similar to Kolb's.

Each of the learning styles reviewed provides some practical implications for designing adaptive instruction. However, there is not yet sufficient empirical evidence to support the value of learning styles or a reliable method for measuring the different learning styles.

25.4.1.4 Prior Knowledge. Glaser and Nitko (1971) suggested that the behaviors that need to be measured in adaptive instruction are those that are predictive of immediate learning success with a particular instructional technique. Because prior achievement measures relate directly to the instructional task, they should therefore provide a more valid and reliable basis for determining adaptations than other aptitude variables.

The value of prior knowledge in predicting the student's achievement and needs of instructional supports has been demonstrated in many studies (e.g., Ross & Morrison, 1988). Research findings have shown that the higher the level of prior achievement, the less the instructional support required to accomplish the given task (e.g., Abramson & Kagen, 1975; Salomon, 1974; Tobias, 1973; Tobias & Federico, 1984; Tobias & Ingber, 1976). Furthermore, prior knowledge has a substantial linear relationship with interest in the subject (Tobias, 1994).

25.4.1.5 Anxiety. Many studies have shown that students with high test anxiety performed poorly on tests in comparison to students with low test anxiety (see Sieber, O'Neil, & Tobias, 1977; Tobias, 1987). Since research findings suggest that high anxiety interferes with the cognitive processes that control learning, procedures for reducing the anxiety level have been investigated. For example, Deutsch and Tobias (1980) found that highly anxious students who had options to review study materials (e.g., videotaped lessons) during learning showed higher achievement than other highly anxious students who did not have the review option. Under an assumption that anxiety and study skills have complementary effects, Tobias (1987) proposed a research hypothesis in an ATI paradigm: "Test-anxious students with poor study skills would learn optimally from a program addressing both anxiety reduction and study skills training. On the other hand, test-anxious students with effective study skills would profit optimally from programs emphasizing anxiety reduction without the additional study skill training" (p. 223). However, more studies are needed to investigate specific procedures or methods for reducing anxiety before guidelines for adaptive instructional design can be made.

25.4.1.6 Achievement Motivation. Motivation is an associative network of affectively toned personality characteristics such as self-perceived competence, locus of control, and anxiety (McClelland, 1965). Thus, understanding and incorporating the interactive roles of motivation with cognitive process variables during instruction are important. However, little research evidence is available for understanding the interactions between the affective and the cognitive variables, particularly individual differences in the interactions.

Although motivation as the psychological determinant of learning achievement has been emphasized by many researchers, research evidence suggests that it has to be activated for each task (Weiner, 1990). According to Snow (1986), students achieve their optimal level of performance when they have an intermediate level of motivation to achieve success and to avoid failure. Lin and McKeachie (1999) suggested that intrinsically motivated students engage in the task more intensively and show better performance than extrinsically motivated students. However, some studies showed opposite results (e.g., Frase, Patrick, & Schumer, 1970). The contradictory findings suggest possible interaction effects of different types of motivation with different students. For example, the intrinsic motivation may be more effective for students who are strongly goal oriented, like adult learners, while extrinsic motivation may be better for students who study because they have to, like many young children.

Entwistle's (1981) classification of student-motivation orientation provides more hints for adapting instruction to the student's motivation state. He identified three types of students based on motivation orientation styles: (a) meaning-oriented students, who are internally motivated by academic interest; (b) reproducing-oriented students, who are extrinsically motivated by fear of failure; and (c) achieving-oriented students, who are motivated primarily by hope for success. Meaning-oriented students are more likely to adopt a holist learning strategy that requires deep cognitive processing, whereas reproduction-

oriented students tend to adopt a serialist strategy that requires relatively shallow cognitive processing (Schmeck, 1988). Achieving-oriented students are likely to adopt either type of learning strategy depending on the given learning content and situation. However, the specific roles of motivation in learning have not been well understood, particularly in relation to the interactions with the student's other characteristics, task, and learning conditions. Without understanding the interactions between motivation and other variables, including instructional strategies, simply adapting instruction to the student's motivation may not be useful.

Tobias (1994) examined student interest in a specific subject and its relations with prior knowledge and learning. Interest, however, is not clearly distinguishable from motivation because interest seems to originate or stimulate intrinsic motivation, and external motivators (e.g., reward) may stimulate interest. Nevertheless, Keller and his associates (Astleitner & Keller, 1995) developed a framework for adapting instruction to the learner's motivational state in computer-assisted instructional environments. They proposed a six-level motivational adaptability from fixed feedback that provides the same instruction to all students regardless of the differences in their motivational states to adaptive feedback that provides different instructional treatments based on the individual learner's motivational state represented in the computer-based instructional process.

25.4.1.7 Self-Efficacy. Self-efficacy influences people's intellectual and social behaviors, including academic achievement (Bandura, 1982). Because self-efficacy is a student's evaluation of his or her own ability to perform a given task, the student may maintain widely varying senses of self-efficacy, depending on the context (Gallagher, 1994). According to Schunk (1991), self-efficacy changes with experiences of success or failure in certain tasks. A study by Hoge, Smith, and Hanson (1990) showed that feedback from teachers and grades received in specific subjects were important factors for the student's academic self-efficacy. Although many positive aspects of high self-esteem have been discussed, few studies have been conducted to investigate the instructional effect of self-efficacy in the ATI paradigm. Zimmerman and Martinez-Pons (1990) suggested that students with high verbal and mathematical self-efficacy used more self-regulatory and metacognitive strategies in learning the subject. Although it is clear that self-regulatory and metacognitive learning strategies have a positive relationship with students' achievement, this study seems to suggest that the intellectual ability is a more primary factor than self-esteem in the selection of learning strategies. More research is needed to find factors contributing to the formation of self-esteem, relationships between self-efficacy and other motivational and cognitive variables influencing learning processes, and strategies for modifying self-efficacy. Before studying these questions, investigating specific instructional strategies for low and high self-efficacy students in an ATI paradigm may not be fruitful.

In addition to the variables just discussed, many other individual difference variables (e.g., locus of control, cognitive development stages, cerebral activities and topological localization of brain hemisphere, and personality variables) have been studied in relation to learning and instruction. Few studies, however,

TABLE 25.1. A Taxonomy of Instructional Strategies
(Park, 1983; Seidel et al., 1989)

<i>Preinstructional Strategies</i>	
1. Instructional objective Terminal objectives and enabling objectives Cognitive objectives vs. behavioral objectives Performance criterion and condition specifications	
2. Advance organizer Expository organizer vs. comparative organizer Verbal organizer vs. pictorial organizer	
3. Overview Narrative overview Topic listing Orienting questions	
4. Pretest Types of test (e.g., objective—true—false, multiple-choice, matching—vs. subjective—short answer, essay) Order of test item presentation (e.g., random, sequence, response sensitive) Item replacement (e.g., with or without replacement of presented items) Timing (e.g., limited vs. unlimited) Reference (e.g., criterion-reference vs. norm-reference)	
<i>Knowledge Presentation Strategies</i>	
1. Types of knowledge presentation Generality (e.g., definition, rules, principles) Instance: diversity and complexity (e.g., example and nonexample problems) Generality help (e.g., analytical explanation of generality) Instance help (e.g., analytical explanation of instance)	
2. Formats of knowledge presentation Enactive, concrete physical representation Iconic, pictorial/graphic representation Symbolic, abstract verbal, or notational representation	
3. Forms of knowledge presentation Expository, statement form Interrogatory, question form	
4. Techniques for facilitating knowledge acquisition Mnemonic Metaphors and analogies Attribute isolations (e.g., coloring, underlining) Verbal articulation Observation and emulation	
<i>Interaction Strategies</i>	
1. Questions Level of questions (e.g., understanding/idea vs. factual information) Time of questioning (e.g., before or after instruction) Response mode required (e.g., selective vs. constructive; overt vs. covert)	
2. Hints and prompts Formal, thematic, algorithmic, etc. Scaffolding (e.g., gradual withdraw of instructor supports) Reminder and refreshment	
3. Feedback Amount of information (e.g., knowledge of results, analytical explanation, algorithmic feedback, reflective comparison) Time of feedback (e.g., immediate vs. delayed feedback) Type of feedback (e.g., cognitive/informative feedback vs. psychological reinforcing)	

Instructional Control Strategies

1. Sequence
 - Linear`
 - Branching`
 - Response sensitive
 - Response sensitive plus aptitude matched
2. Control options
 - Program control
 - Learner control
 - Learner control with advice
 - Condition-dependent mixed control

Postinstructional Strategies

1. Summary
 - Narrative review
 - Topic listing
 - Review questions
2. Postorganizer
 - Conceptual mapping
 - Synthesizing
3. Posttest
 - Types of test (e.g., objective—true—false, multiple choice, matching—vs. subjective—short answer, essay)
 - Order of test item presentation (e.g., random, sequence, response sensitive)
 - Item replacement (e.g., with or without replacement of presented items)
 - Timing (e.g., limited vs. unlimited)
 - Reference (e.g., criterion reference vs. norm reference)

Note. This listing of instructional strategies is not exhaustive and the classifications are arbitrary. From *Instructional Strategies: A Hypothetical Taxonomy* (Technical Report No. 3), by O. Park, 1983, Minneapolis, MN: Control Data Corp. Adapted with permission.

have provided feasible suggestions for adapting instruction to individual differences in these variables.

25.4.2 A Taxonomy of Instructional Strategies

Although numerous teaming and instructional strategies have been studied (e.g., O'Neil, 1978; Weinstein, Goetz & Alexander, 1988), selecting a specific strategy for a given instructional situation is difficult because its effect may be different for different instructional contexts. It is particularly true for adaptive instruction. Thus, instructional strategies should be selected and designed with the consideration of many variables uniquely involved in a given context. To provide a general guideline for selecting instructional strategies, Jonassen (1988) proposed a taxonomy of instructional strategies corresponding to different processes of cognitive learning. After identifying four stages of the learning process (recall, integration, organization, and elaboration) and related learning strategies for each stage, he identified specific instructional activities for facilitating the learning process. Also, he identified different strategies for monitoring different types of cognitive operations (i.e., planning, attending, encoding, reviewing, and evaluating).

Park (1983) also proposed a taxonomy of instructional strategies (Table 25.1) for different instructional stages or activities (i.e., preinstructional strategies, knowledge presentation strategies, interaction strategies, instructional control strategies,

and postinstructional strategies). However, these taxonomies are identified from the author's subjective analysis of learning and instructional processes and do not provide direct or indirect suggestions for selecting instructional strategies in ATI research or adaptive instructional development.

25.4.3 Limitations of Aptitude Treatment Interactions

In the three decades since Cronbach (1957) made his proposal, relatively few studies have found consistent results to support the paradigm or made a notable contribution to either instructional theory or practice. As several reviews of ATI research (Berliner & Cohen, 1983; Cronbach & Snow, 1977; Tobias, 1976) have pointed out, the measures of intellectual abilities and other aptitude variables were used in a large number of studies to investigate their interactions with a variety of instructional treatments. However, no convincing evidence was found to suggest that such individual differences were useful variables for differentiating alternative treatments for subjects in a homogeneous age group, although it was believed that the individual difference measures were correlated substantially with achievement in most school-related tasks (Glaser & Resnick, 1972; Tobias, 1987).

The unsatisfactory results of ATI research have prompted researchers to reexamine the paradigm and assess its effectiveness. A number of difficulties in the ATI approach are viewed by Tobias (1976, 1987, 1989) as a function of past reliance on what he terms the alternative abilities concept. Under this concept, it is assumed that instruction is divided into input, processing, and output variables. The instruction methods, which form the input of the model, are hypothesized to interact with different psychological abilities (processing variables), resulting in certain levels of performance (or outcomes) on criterion tests. According to Tobias, however, several serious limitations of the model often prevent the occurrence of the hypothesized relations, as follows.

1. The abilities assumed to be most effective for a particular treatment may not be exclusive; consequently, one ability may be used as effectively as another ability for instruction by a certain method (see Cronbach & Snow, 1977).
2. Abilities required by a treatment may shift as the task progresses so that the ability becomes more or less important for one unit (or lesson) than for another (see Burns, 1980; Federico, 1983).
3. ATIs validated for a particular task and subject area may not be generalizable to other areas. Research has suggested that ATIs may well be highly specific and vary for different kinds of content (see Peterson, 1977; Peterson & Janicki, 1979; Peterson, Janicki, & Swing, 1981).
4. ATIs validated in laboratory experiments may not be applicable to actual classroom situations.

Another criticism is that ATI research has tended to be overly concerned with exploration of simple input/output relations between measured traits and learning outcomes. According

to this criticism, a thorough understanding of the psychological process in learning a specific task is a prerequisite to the development theory on the ATIs (DiVesta, 1975). Since individual difference variables are difficult to measure, the test validity can also be a problem in attempting to adapt instruction to general student characteristics.

25.4.4 Achievement–Treatment Interactions

To reduce some of the difficulties in the ATI approach, Tobias (1976) proposed an alternative model, achievement–treatment interactions. Whereas the ATI approach stresses relatively permanent dispositions for learning as assessed by measures of aptitudes (e.g., intelligence, personality, and cognitive styles), achievement–treatment interactions represent a distinctly different orientation, emphasizing task-specific variables relating to prior achievement and subject-matter familiarity. This approach stresses the need to consider interactions between prior achievement and performance on the instructional task to be learned. Prior achievement can be assessed rather easily and conveniently through administration of pretests or through analysis of students' previous performance on related tasks. Thus, it eliminates many potential sources of measurement error, which has been a problem in ATI research, since the type of abilities to be assessed would be, for the most part, clear and unambiguous.

Many studies (e.g., see Tobias 1973, 1976; Tobias & Federico, 1984) confirmed the hypothesis that the lower the level of prior achievement is, the more the instructional support is required to accomplish the given task, and vice versa. However, a major problem in the ATI approach, that learner abilities and characteristics fluctuate during instruction, is still unsolved in the achievement–treatment interaction. The treatments investigated in the studies of this approach were not generated by systematic analysis of the kind of psychological processes called on in particular instructional methods, and individual differences were not assessed in terms of these processes (Glaser, 1972). In addition to the inability to accommodate shifts in the psychological processes active during or required by a given task, the achievement–treatment interaction has another problem: In this model, some useful information may be lost by discounting possible contribution of factors such as intellectual ability, cognitive style, anxiety, and motivation.

25.4.5 Cognitive Processes and ATI Research

The limitation of aptitudes measured prior to instruction in predicting the student's learning needs suggests that the cognitive processes intrinsic to learning should be paramount considerations in adapting instructional techniques to individual differences. However, psychological testing developed to measure and classify people according to abilities and aptitudes has neglected to identify the internal processes that underlie such classifications (Federico, 1980).

According to Tobias (1982, 1987), learning involves two types of cognitive processes: (a) macroprocesses, which are relatively molar processes, such as mental tactics (Derry & Murphy, 1986), and are deployed under the student's volitional

control; and (b) microprocesses, which are relatively molecular processes, such as the manipulation of information in short-term memory, and are less readily altered by students. Tobias (1989) assumed that unless the instructional methods examined in ATI research induce students with different aptitudes to use different types of macroprocesses, the expected interactions would not occur. To validate this assumption, Tobias (1987, 1989) conducted a series of experiments in rereading comprehension using computer-based instruction (CBI). In the experiments, students were given various options to employ different macroprocesses through the presentation of different instructional activities (e.g., adjunct questions, feedback, various review requirements, instructions to think of the adjunct question while reviewing, and rereading with external support). In summarizing the findings from the experiments, Tobias (1989) concluded that varying instructional methods does not lead to the use of different macrocognitive processes or to changes in the frequency with which different processes are used. Also, the findings showed little evidence that voluntary use of macrocognitive processes is meaningfully related to student characteristics such as anxiety, domain-specific knowledge, and reading ability. Although some of these findings are not consistent with previous studies that showed a high correlation between prior knowledge and the outcome of learning, they explain the reasons for the inconsistent findings in ATI research.

Based on the results of the experiments and the review of relevant studies, Tobias (1989) suggested that researchers should not assume student use of cognitive processes, no matter how clearly these appear to be required or stimulated by the instructional method. Instead, some students should be trained or at least prompted to use the cognitive processes expected to be evoked by instructional methods, whereas such intervention should be omitted for others (p. 220). This suggestion requires a new paradigm for ATI research that specifies not only student characteristics and alternative instructional methods for teaching students with different characteristics but also strategies for prompting the student to use the cognitive processes required in the instructional methods. This suggestion, however, would make ATI research more complex without being able to produce consistent findings. For example, if an experiment did not produce the expected interaction, it would be virtually impossible to find out whether the result came from the ineffectiveness of the instructional method or the failure of the prompting strategy to use the instructional method.

25.4.6 Learner Control

An alternative approach to adaptive instruction is learner control, which gives learners full or partial control over the process or style of instruction they receive (Snow, 1980). Individual students are different in their abilities for assessing the learning requirements of a given task, their own learning abilities, and instructional options available to learn the given task. Therefore, it can be considered within the ATI framework, although the decision-making authority required for the learning assessment and instructional prescription is changed to the student from the instructional agent (human teacher or media-based tutor).

Snow (1980) divided the degree of learner control into three levels depending on the imposed and elected educational goals and treatments: (a) complete independence, self-direction, and self-evaluation; (b) imposed tasks, but with learner control of sequence, scheduling, and pace of learning; and (c) fixed tasks, with learner control of pace. Numerous studies have been conducted to test the instructional effects of learner control and specific instructional strategies that can be effectively used in learner-control environments. The results have provided some important implications for developing adaptive systems: Individual differences play an important role in the success of learner control strategy, some learning activities performed during the instruction are closely related to the effectiveness of learner control, and the learning activities and effects of learner control can be predicted from the premeasured aptitude variables (Snow, 1980). For example, a study by Shin, Schallert, and Savenye (1994) showed that limited learner control and advisement during instruction were more effective for low-prior knowledge students, while high-prior knowledge students did equally well in both full and limited learner-control environments with or without advisement. These results suggest that learner control should be considered both a dimension along which instructional treatments differ and a dimension characteristic of individual differences among learners (Snow, 1980). However, research findings in learner control are not consistent, and many questions remain to be answered in terms of the learner-control activities and metacognitive processes. For example, more research is needed in terms of learner-control strategies related to assessment of knowledge about the domain content, ability to learn, selection and processing of learning strategies, etc.

25.4.7 An Eight-Step Model for Designing ATI Courseware

As just reviewed, findings in ATI research suggest that it is premature or impossible to assign students with one set of characteristics to one instructional method and those with different characteristics to another (Tobias, 1987). However, faith in adaptive instruction using the ATI model is still alive because of the theoretical and practical implications of ATI research.

Despite the inconclusive research evidence and many unresolved issues in the ATI approach, Carrier and Jonassen (1988) proposed an eight-step model to provide practical guidance for applying the ATI model to the design of CBI courseware. The eight steps are as follows: (1) Identify objectives for the courseware, (2) specify task characteristics, (3) identify an initial pool of learner characteristics, (4) select the most relevant learner characteristics, (5) analyze learners in the target population, (6) select final differences (in the learner characteristics), (7) determine how to adapt instruction, and (8) design alternative treatments. This model is basically a modified systems approach to instructional development Dick & Carey, 1985. (Gagné & Briggs, 1979). This model proposes to identify specific learner characteristics of individual students for the given task, in addition to their general characteristics. For the use of this model, Carrier and Jonassen (1988) listed important individual variables that influence learning: (a) aptitude variables,

including intelligence and academic achievement; (b) prior knowledge; (c) cognitive styles; and (d) personality variables, including intrinsic and extrinsic motivation, locus of control, and anxiety (see Carrier & Jonassen, 1988, P. 205). For instructional adaptation, they recommended several types of instructional matches: remedial, capitalization/preferential, compensatory, and challenge.

This model seemingly has practical value. Without theoretically coherent and empirically traceable matrices that link the different learner variables, the different types and levels of learning requirements in different tasks, and different instructional strategies, however, the mere application of this model may not produce results much different from those with nonadaptive instructional systems. ATI research findings suggest that varying instructional methods does not necessarily invoke different types or frequencies of cognitive processing required in learning the given task, nor are individual difference measures consistently related to such processing (Tobias, 1989). Furthermore, the application of Carrier and Jonassen's (1988) model in the development and implementation of courseware would be very difficult because of the amount of work required in identifying, measuring, and analyzing the appropriate learner characteristics and in developing alternative instructional strategies.

25.5 MICRO-ADAPTIVE INSTRUCTIONAL MODELS

Although the research evidence has failed to show the advantage of the ATI approach for the development of adaptive instructional systems, research to find aptitude constructs relevant to learning, learning and instructional strategies, and their interactions continues. However, the outlook is not optimistic for the development of a comprehensive ATI model or set of principles for developing adaptive instruction that is empirically traceable and theoretically coherent in the near-future. Thus, some researchers have attempted to establish micro-adaptive instructional models using on-task measures rather than pretask measures. On-task measures of student behavior and performance, such as response errors, response latencies, and emotional states, can be valuable sources for making adaptive instructional decisions during the instructional process. Such measures taken during the course of instruction can be applied to the manipulation and optimization of instructional treatments and sequences on a much more refined scale (Federico, 1983). Thus, micro-adaptive instructional models using on-task measures are likely to be more sensitive to the student's needs.

A typical example of micro-adaptive instruction is one-on-one tutoring. The tutor selects the most appropriate information to teach based on his or her judgment of the student's learning ability, including prior knowledge, intellectual ability, and motivation. Then the tutor continuously monitors and diagnoses the student's learning process and determines the next instructional actions. The instructional actions can be questions, feedback, explanations, or others that maximize the student's learning. Although the instructional effect of one-on-one tutoring has been fully recognized for a long time and empirically

proven (Bloom, 1984; Kulik, 1982), few systematic guidelines have been developed. That is, most tutoring activities are determined by the tutor's intuitive judgments about the student's learning needs and ability for the given task. Also, one-on-one tutoring is virtually impossible for most educational situations because of the lack of both qualified tutors and resources.

As the one-on-one tutorial process suggests, the essential element of micro-adaptive instruction is the ongoing diagnosis of the student's learning needs and the prescription of instructional treatments based on the diagnosis. Holland (1977) emphasized the importance of the diagnostic and prescriptive process by defining adaptive instruction as a set of processes by which individual differences in student needs are diagnosed in an attempt to present each student with only those teaching materials necessary to reach proficiency in the terminal objectives of instruction. Landa (1976) also said that adaptive instruction is the diagnostic and prescriptive processes aimed at adjusting the basic learning environment to the unique learning characteristics and needs of each learner. According to Rothen and Tennyson (1978), the diagnostic process should assess a variety of learner indices (e.g., aptitudes and prior achievement) and characteristics of the learning task (e.g., difficulty level, content structure, and conceptual attributes). Hansen, Ross, and Rakow (1977) described the instructional prescription as a corrective process that facilitates a more appropriate interaction between the individual learner and the targeted learning task by systematically adapting the allocation of learning resources to the learner's aptitudes and recent performance.

Instructional researchers or developers have different views about the variables, indices, procedures, and actions that should be included in the diagnostic and the prescriptive processes. For example, Atkinson (1976) says that an adaptive instructional system should have the capability of varying the sequence of instructional action as a function of a given learner's performance history. According to Rothen and Tennyson (1977), a strategy for selecting the optimal amount of instruction and time necessary to achieve a given objective is the essential ingredient in an adaptive instructional system. This observation suggests that different adaptive systems have been developed to adapt different features of instruction to learners in different ways.

Micro-adaptive instructional systems have been developed through a series of different attempts beginning with programmed instruction to the recent application of artificial intelligence (AI) methodology for the development of intelligent tutoring systems (ITSs).

25.5.1 Programmed Instruction

Skinner has generally been considered the pioneer of programmed instruction. However, three decades earlier than Skinner (1954, 1958), Pressey (1926) used a mechanical device to assess a student's achievement and to provide further instruction in the teaching process. The mechanical device, which used a keyboard, presented a series of multiple-choice questions and required the student to respond by pressing the appropriate key. If the student pressed the correct key to answer the question, the device would present the next

question. However, if the student pressed a wrong key, the device would ask the student to choose another answer without advancing to the next question. Using Thorndike's (1913) "Law of Effect" as the theoretical base for the teaching methodology incorporated in his mechanical device, Pressey (1927) claimed that its purpose was to ensure mastery of a given instructional objective. If the student correctly answered two questions in succession, mastery was accomplished, and no additional questions were given. The device also recorded responses to determine whether the student needed more instruction (further questions) to master the objective. According to Pressey, this made use of a modified form of Thorndike's "law of exercise." Little's (1934) study demonstrated the effectiveness of Pressey's testing-drill device against a testing-only device.

Skinner (1954) criticized Pressey's work by stating that it was not based on a thorough understanding of learning behavior. However, Pressey's work contained some noticeable instructional principles. First, he brought the mastery learning concept into his programmed instructional device, although the determination of mastery was arbitrary and did not consider measurement or testing theory. Second, he considered the difficulty level of the instructional objectives, suggesting that more difficult objectives would need additional instructional items (questions) for the student to reach mastery. Finally, his procedure exhibited a diagnostic characteristic in that, although the criterion level was based on intuition, he determined from the student's responses whether or not more instruction was needed.

Using Pressey's (1926, 1927) basic idea, Skinner (1954, 1958) designed a teaching machine to arrange contingencies of reinforcement in school learning. The instructional program format used in the teaching machine had the following characteristics: (a) It was made up of small, relatively easy-to-learn steps; (b) the student had an active role in the instructional process; and (c) positive reinforcement was given immediately following each correct response. In particular, Skinner's (1968) linear programmed instruction emphasized an individually different learning rate. However, the programmed material itself was not individualized since all students received the same instructional sequence (Cohen, 1963). In 1959, Pressey criticized this nonadaptive nature of the Skinnerian programmed instruction.

The influx of technology influenced Crowder's (1959) procedure of intrinsic programming with provisions for branching able students through the same material more rapidly than slower students, who received remedial frames whenever a question was missed. Crowder's intrinsic program was based totally on the nature of the student's response. The response to a particular frame was used both to determine whether the student learned from the preceding material and to determine the material to be presented next. The student's response was thought to reflect his or her knowledge rate, and the program was designed to adapt to that rate. Having provided only a description of his intrinsic programming, however, Crowder revealed no underlying theory or empirical evidence that could support its effectiveness against other kinds of programmed instruction. Because of the difficulty in developing tasks that required review sections for each alternative answer, Crowder's procedure was not widely used in instructional situations (Merrill, 1971).

In 1957, Pask described a perceptual motor training device in which differences in task difficulty were considered for different learners. The instructional target was made progressively more difficult until the student made an error, at which point the device would make the target somewhat easier to detect. From that point, the level of difficulty would build again. Remediation consisted of a step backward on a difficulty dimension to provide the student with further practice on the task. Pask's (1960a, 1960b) Solartron Automatic Keyboard Instructor (SAKI) was capable of electronically measuring the student's performance and storing it in a diagnostic history that included response latency, error number, and pattern. On the basis of this diagnostic history, the machine prescribed the exercises to be presented next and varied the rate and amount of material to be presented in accordance with the proficiency. Lewis and Pask (1965) demonstrated the effectiveness of Pask's device by testing the hypothesis that adjusting difficulty level and amount of practice would be more effective than adjusting difficulty level alone. Though the application of the device was limited to instruction of perceptual motor tasks, Pask (1960a) described a general framework for the device that included instruction of conceptual as well as perceptual motor tasks.

As described, most early programmed instruction methods relied primarily on intuition of the school learning process rather than on a particular model or theory of learning, instruction, or measurement. Although some of the methods were designed on a theoretical basis (for example, Skinner's teaching machine), they were primitive in terms of the adaptation of the learning environment to the individual differences of students. However, programmed instruction did provide some important implications for the development of more sophisticated instructional strategies made possible by the advance in computer technology.

25.5.2 Microadaptive Instructional Models

Using computer technology, a number of microadaptive instructional models have been developed. An adaptive instructional model differs from programmed instruction techniques in that it is based on a particular model or theory of learning, and its adaptation of the learning environment is rather sophisticated, whereas the early programmed instruction was based primarily on intuition and its adaptation was primitive. Unlike macroadaptive models, the microadaptive model uses the temporal nature of learner abilities and characteristics as a major source of diagnostic information on which an instructional treatment is prescribed. Thus, an attribute of a microadaptive model is its dynamic nature as contrasted with a macroadaptive model. A typical microadaptive model includes more variables related to instruction than a macroadaptive model or programmed instruction. It thus provides a better control process than a macroadaptive model or programmed instruction in responding to the student's performance with reference to the type of content and behavior required in a learning task (Merrill & Boutwell, 1973).

As described by Suppes, Fletcher, and Zanottie (1976), most microadaptive models use a quantitative representation

and trajectory methodology. The most important feature of a microadaptive model relates to the timeliness and accuracy with which it can determine and adjust learning prescriptions during instruction. A conventional instructional method identifies how the student answers but does not identify the reasoning process that leads the student to that answer. An adaptive model, however, relies on different processes that lead to given outcomes. Discrimination between the different processes is possible when on-task information is used. The importance of the adaptive model is not that the instruction can correct each mistake but that it attempts to identify the psychological cause of mistakes and thereby lower the probability that such mistakes will occur again.

Several examples of microadaptive models are described in the following section. Although some of these models are a few decades old, an attempt was made to provide a rather detailed review because the theoretical bases and technical (nonprogramming) procedures used in these models are still relevant and valuable in identifying research issues related to adaptive instruction and in designing future adaptive systems. Particularly, having considered that some theoretical issues and ideas proposed in these models could not be fully explored because of the lack of computer power at that time, the review may provide some valuable research and development agenda.

25.5.2.1 Mathematical Model. According to Atkinson (1972), an optimal instructional strategy must be derived from a model of learning. In mathematical learning theory, two general models describe the learning process: a linear (or incremental) model and an all-or-none (or one element) model. From these two models, Atkinson and Paulson (1972) deduced three strategies for prescribing the most effective instructional sequence for a few special subjects, such as foreign-language vocabulary (Atkinson, 1968, 1974, 1976; Atkinson & Fletcher, 1972).

In the linear model, learning is defined as the gradual reduction in probability of error by repeated presentations of the given instructional items. The strategy in this model orders the instructional materials without taking into account the student's responses or abilities, since it is assumed that all students learn with the same probability. Because the probability of student error on each item is determined in advance, prediction of his or her success depends only on the number of presentations of the items.

In the all-or-none model, learning an item is not all gradual but occurs on a single trial. An item is in one of two states, a learned state or an unlearned state. If an item in the learned state is presented, the correct response is always given; however, if an item in the unlearned state is presented, an incorrect response is given unless the student makes a correct response by guessing. The optimal strategy in this model is to select for presentation the item least likely to be in the learned state, because once an item has been learned, there is no further reason to present it again. If an item in the unlearned state is presented, it changes to the learned state with a probability that remains constant throughout the procedure. Unlike the strategy in the linear model, this strategy is response sensitive. A student's response protocol for a single item provides a good index of the likelihood of that item's being in the

learned state (Groen & Atkinson, 1966). This response-sensitive strategy used a dynamic programming technique (Smallwood, 1962).

On the basis of Norman's (1964) work, Atkinson and Paulson (1972) proposed the random-trial incremental model, a compromise between the linear and the all-or-none models. The instructional strategy derived for this model is parameter dependent, allowing the parameters to vary with student abilities and item difficulty. This strategy determines which item, if presented, has the best expected immediate gain, using a reasonable approximation (Calfee, 1970). Atkinson and Crothers (1964) assumed that the all-or-none model provided a better account of data than the linear model and that the random-trial increments model was better than either of them. This assumption was supported by testing the effectiveness of the strategies (Atkinson, 1976).

The all-or-none strategy was more effective than the standard linear procedure for spelling instruction, while the parameter-dependent strategy was better than the all-or-none strategy for teaching foreign vocabularies (Lorton, 1972). In the context of instruction, cost-benefit analysis is one of the key elements in a description of the learning process and determination of instructional actions (Atkinson, 1972). In the mathematical adaptive strategies, however, it is assumed that the costs of instruction are equal for all strategies, because the instructional formats and the time allocated to instruction are all the same. If both costs and benefits are significantly variable in a problem, then it is essential that both quantities be estimated accurately. Smallwood (1970, 1971) treated this problem by including a utility function into the mathematical model. Smallwood's (1971) economic teaching strategy is a special form of the all-or-none model strategy, except that it can be applied for an instructional situation in which the instructional alternatives have different costs and benefits.

Townsend (1992) and Fisher and Townsend (1993) applied a mathematical model to the development of a computer simulation and testing system for predicting the probability and duration of student responses in the acquisition of Morse code classification skills. The mathematical adaptive model, however, has never been widely used, probably because the learning process in the model is oversimplified and the applicability is limited to a relatively simple range of instructional contents.

There are criticisms of the mathematical adaptive instructional models. First, the learning process in the mathematical model is oversimplified when implemented in a practical teaching system. Yet it may not be so simple to quantify the transition probability of a learning state and the response probabilities that are uniquely associated with the student's internal states of knowledge and with the particular alternatives for presentation (Glaser, 1976). Although quantitative knowledge about how the variables in the model interact can be obtained, reducing computer decision time has little overall importance if the system can handle only a limited range of instructional materials and objectives, such as foreign-language vocabulary items (Gregg, 1970). Also, the two-state or three-state or n -state model cannot be arbitrarily chosen because the values for transitional probabilities of a learning state can change depending on how one chooses to aggregate over states. The response probabilities may not be assumed to be equally likely in a multiple-choice

test question. This kind of assumption would hold only for homogeneous materials and highly sophisticated preliminary item analyses (Gregg, 1970).

Another disadvantage of the mathematical adaptive model is that its estimates for the instructional diagnosis and prescription cannot be reliable until a significant amount of student and content data is accumulated. For example, the parameter-dependent strategy supposes to predict the performance of other students or the same student on other items from the estimates computed by the logistic equation. However, the first students in an instructional program employing this strategy do not benefit from the program's sensitivity to individual differences in students or items because the initial parameter estimates must be based on data from these students. Thus, the effectiveness of this strategy is questionable unless the instructional program continues over a long period of time.

Atkinson (1972) admitted that the mathematical adaptive models are very simple, and the identification of truly effective strategies will not be possible until the learning process is better understood. However, Atkinson (1972, 1976) contended that an all-inclusive theory of learning is not a prerequisite for the development of optimal procedures. Rather, a model is needed that captures the essential features of that part of the learning process being tapped by a given instructional task.

25.5.2.2 The Trajectory Model: Multiple Regression Analysis Approach. In a typical adaptive instructional program, the diagnostic and prescriptive decisions are frequently made based on the estimated contribution of one or two particular variables. The possible contributions of other variables are ignored. In a trajectory model, however, numerous variables can be included with the use of a multiple regression technique to yield what may be a more powerful and precise predictive base than is obtained by considering a particular variable alone.

The theoretical view in the trajectory model is that the expected course of the adaptive instructional trajectory is determined primarily by generic or trait factors that define the student group. The actual proceeding of the trajectory is dependent on the specific effects of individual learner parameters and variables derived from the task situation (Suppes et al., 1976). Using this theoretical view, Hansen et al. (1977; Ross & Morrison, 1988; Ross & Rakow, 1982) developed an adaptive model that reflects both group and individual indexes and matches them to appropriate changes for both predictions on entry and adjustments during the treatment process. The model was developed to find an optimal strategy for selecting the appropriate number of examples in a mathematical rule-learning task.

Hansen et al. (1977) assessed their trajectory adaptive model with a validation study that supported the basic tenets of the model. A desirable number of groups (four) with differential characteristics was found, and the outcomes were as predicted: superior for the adaptive group, highly positive for the cluster group, and poor for the mismatched groups. The outcome of regression analysis revealed that the pretest yielded the largest amount of explained variance within the regression coefficient. The math reading comprehension measures seemed to contribute to the assignment of the broader skill domain involved in

the learning task. However, the two personality measures varied in terms of directions as well as magnitude.

This regression model is apparently helpful in estimating the relative importance of different variables for instruction. However, it does not seem to be a very useful adaptive instructional strategy. Even though many variables can be included in the analysis process, the evaluation study results indicate that only one or two are needed in the instructional prescription process because of the inconsistent or negligible contribution of other variables to the instruction. Unless the number of students to be taught is large, this approach cannot be effective since the establishment of the predictive database in advance requires a considerable number of students, and this strategy cannot be applied to those students who make up the initial database. Furthermore, a new predictive database has to be established whenever the characteristics of the learning task are changed. Transforming the student's score, as predicted from the regression equation, into the necessary number of examples is not strongly justified when a quasi-standard score procedure is used. The decision rules for adjustment of instructional treatment during on-task performance as well as for the initial instructional prescription are entirely arbitrary. Since regression analyses are based on group characteristics, shrinkage of the degrees of freedom due to reduced sample size may raise questions about the value of this approach.

To offset the shortcoming of the regression model, that is limited to the adaptation of instructional amount (e.g., selection of the number of examples in concept or rule learning), Ross and Morrison (1988) attempted to expand its functional scope by adding the capability for selecting the appropriate instructional content based on the student's interest and other background information. This contextual adaptation was based on empirical research evidence that the personalized context based on an individual student's interest and orientation facilitates the student's understanding of the problem and learning of the solution. A field study demonstrated the effectiveness of the contextual adaptation (Ross & Anand, 1986). Ross and Morrison (1988) further extended their idea of contextual adaptation by allowing the system to select different densities (or "detailedness") of textual explanation based on the student's predicted learning needs. The predicted learning needs were estimated using a multiple regression model just described. An evaluation study showed the superior effect of the adaptation of contextual density over a standard contextual density condition or learner-control condition.

Ross and Morrison's approaches for contextual adaptation alone cannot be considered microadaptive systems because they do not have capability of performing ongoing diagnosis and prescription generation during the task performance. Their diagnostic and prescriptive decisions are made on the basis of preinstructional data. The contextual adaptation approach, however, can be a significant addition to a microadaptive model like the regression analysis approach that has a limited function for adapting the quality of instruction, including the content. Although we presume that the contextual adaptation approaches were originally developed with the intent to incorporate them in the regression analysis model, this has not yet been fully accomplished.

25.5.2.3 The Bayesian Probability Model. The Bayesian probability model employs a two-step approach for adapting instruction to individual students. After the initial assignment of the instructional treatment is made on the basis of preinstructional measures (e.g., pretest scores), the treatment prescription is continuously adjusted according to student on-task performance data. To operationalize this approach in CBI, a Bayesian statistical model was used. Baye's theorem of conditional probability seems appropriate for the development of an adaptive instructional system because it can predict the probability of mastery of the new learning task from student preinstructional characteristics and then continuously update the probability according to the on-task performance data (Rothen & Tennyson, 1978; Tennyson & Christensen, 1988). Accordingly, the instructional treatment is selected and adjusted.

The functional operation of this model is related to guidelines described by Novick and Lewis (1974) for determining the minimal length of a test adequate to provide sufficient information about the learner's degree of mastery of behavior being tested. Novick and Lewis procedure uses a pretest on a set of objectives. From this pretest, the initial prior estimate of a student's ability per objective is combined in a Bayesian manner with information accumulated from previous students to generate a posterior estimate of the student's probability of mastery of each objective. This procedure generates a table of values for different test lengths for the objectives and selects the number of test items from this table that seems adequate to predict mastery of each objective. Rothen and Tennyson (1978) modified Novick and Lewis (1974) model in such a way that a definite rule or algorithm selects an instructional prescription from the table of generated values. In addition, this prescription is updated according to individual student's on-task learning performance.

Studies by Tennyson and his associates (see Tennyson & Christensen, 1988) demonstrated the effectiveness of the Bayesian probabilistic adaptive model in selecting the appropriate number of examples in concept learning. Posttest scores showed that the adaptive group was significantly better than the nonadaptive groups. Particularly, students in the adaptive group required significantly less learning time than students in the nonadaptive groups. This model was also effective in selecting the appropriate amount of instructional time for each student based on his or her on-task performance (Tennyson & S. Park, 1984; Tennyson, Park, & Christensen, 1985).

If the instructional system uses mastery learning as its primary goal and adjustment of the instructional treatment is critical for learning, this model may be ideal. Another advantage of this model is that no assumption regarding the instructional item homogeneity (in content or difficulty) is needed. A questionable aspect of the model, however, is whether or not variables other than prior achievement and on-task performance can be effectively incorporated. Another difficulty of this model is how to make a prior distribution from the pretest score and historical information collected from previous students. Although Hambleton and Novick (1973) suggested the possibility of using the student's performance level on other referral tasks for the historical data, until enough historical data are accumulated, this model cannot be utilized. Also, the application of this model is limited to rather simple tasks such as concept and rule learning.

Park and Tennyson (1980, 1986) extended the function of the Bayesian model by incorporating a sequencing strategy in the model. Park and Tennyson (1980) developed a responsive-sensitive strategy for selecting the presentation order of examples in concept learning from the analysis of cognitive learning requirements in concept learning (Tennyson & Park, 1982). Studies by Park and Tennyson (1980, 1986) and Tennyson, Park, and Christensen (1985) showed that the response-sensitive sequence not only was more effective than the non-response-sensitive strategy but also reduced the necessary number of examples that the Bayesian model predicted for the student. Also, Park and Tennyson's studies found that the value of the pretask information decreases as the instruction progresses. In contrast, the contribution of the on-task performance data to the model's prediction increases as the instruction progresses.

25.5.2.4 The Structural and Algorithmic Approach. The optimization of instruction in Scandura's (1973, 1977a, 1977b, 1983) structural learning theory consists of finding optimal trade-offs between the sum of the values of the objectives achieved and the total time required for instruction. Optimization will involve balancing gains against costs (a form of cost-benefit analysis). This notion is conceptually similar to Atkinson's (1976) and Atkinson and Paulson's (1972) cost-benefit dimension of instructional theory, Smallwood's (1971) economic teaching strategy, and Chant and Atkinson's (1973) optimal allocation of instructional efforts. In structural learning theory, structural analysis of content is especially important as a means of finding optimal trade-offs. According to Scandura (1977a, 1977b), the competence underlying a given task domain is represented in terms of sets of processes, or rules for problem solving. Analysis of content structure is a method for identifying those processes.

Given a class of tasks, the structural analysis of content involves (a) sampling a wide variety of tasks, (b) identifying a set of problem-solving rules for performing the tasks (such as an ideal student in the target population might use), (c) identifying parallels among the rules and devising higher-order rules that reflect these parallels, (d) constructing more basic rule sets that incorporate higher-order and other rules, (e) testing and refining the resulting rule set on new problems, and (f) extending the rule set when necessary so that it accounts for both familiar and novel tasks in the domain. This method may be reapplied to the rule set obtained and repeated as many times as desired. Each time the method is applied, the resulting rule set tends to become more basic in two senses: First, the individual rules become more simple; and second, the new rule set as a whole has greater generating power for solving a wider variety of problems.

According to Scandura (1977a) and Wulfeck and Scandura (1977), the instructional sequence determined by this algorithmic procedure is optimal. This algorithmically designed sequence was superior to learner-controlled and random sequences in terms of the performance scores and the problem solution time (Wulfeck & Scandura, 1977). Also, Scandura and Dumin (1977) reported that a testing method based on the algorithmic sequence could assess the student's performance potentially more accurately with fewer test items and less time than a

domain-reference generation procedure and a hierarchical item generation procedure. Since the algorithmic sequence is determined only by the structural characteristics of given problems and the prior knowledge of the target population (not individual students), the instructional process in structural learning theory is not adaptive to individual differences of the learner. Stressing the importance of individual differences in his structural learning theory, Scandura (1977a, 1977b, 1983) states that what is learned at each stage depends on both what is presented to the learner and what the learner knows. Based on the algorithmic sequence in the structural learning theory, Scandura and his associates (Scandura & Scandura, 1988) developed a rule-based CBI system. However, there has been no combined study of algorithmic sequence and individual differences that might show how individual differences could be used to determine the algorithmic sequences.

Landa's (1976) structural psychodiagnostic method may be well combined with Scandura's algorithmic sequence strategy to adapt the sequential procedure to individual differences that would emerge as the student learns a given task using the predetermined algorithmic sequence. According to Landa (1976), the structural psychodiagnostic method can identify the specific defects in the student's psychological mechanisms of cognitive activity by isolating the attributes of the given learning task that define the required actions and then joining these attributes with the student's logical operations.

25.5.2.5 Other Microadaptive Models. For the last two decades, some other micro-adaptive instructional systems have been developed to optimize the effectiveness or efficiency of instruction for individual students. For example, McCombs and McDaniel (1981) developed a two-step (macro and micro) adaptive system to accommodate the multivariate nature of learning characteristics and idiosyncratic learning processes in the ATI paradigm. They identified the important learning characteristics (e.g., reading/reasoning and memory ability, anxiety, and curiosity) from the results of multiple stepwise regression analyses of existing student performance data. To compensate for the student's deficiencies in the learning characteristics, they added a number of special-treatment components to the main track of instructional materials. For example, to assist low-ability students in reading comprehension or information-processing skills, schematic visual organizers were added. However, most systems like McComb and McDaniel's are not covered in this review because they do not have true on-task adaptive capability, which is the most important criterion for qualification as a microadaptive model. In addition, these systems are task dependent, and the applicability to other tasks is very limited, although the basic principles or ideas of the systems are plausible.

25.5.3 Treatment Variables in Microadaptive Models

As reviewed in the previous section, microadaptive models are developed primarily to adapt two instructional variables: the amount of content to be presented and the presentation sequence of the content. The Bayesian probabilistic model and the multiple regression model are designed to select the amount

of instruction needed to learn the given task. Park and Tennyson (1980, 1986) incorporated sequencing strategies in the Bayesian probability model, and Ross and his associates (Ross & Anand, 1986; Ross & Morrison, 1986) investigated strategies for selecting content in the multiple regression model. Although these efforts showed that other instructional strategies could be incorporated in the model, they did not change the primary instructional variables and the operational procedure of the model. The mathematical model and the structural/algorithmic approach are designed mainly to select the optimal sequence of instruction. According to the Bayesian model and the multiple regression approach, the appropriate amount of instruction is determined by individual learning differences (aptitudes, including prior knowledge) and the individual's specific learning needs (on-task requirements). In the mathematical model, the history of the student's response pattern determines the sequence of instruction. However, an important implication of the structural/algorithmic approach is that the sequence of instruction should be decided by the content structure of the learning task as well as the student's performance history.

The Bayesian model and the multiple regression model use both pretask and on-task information to prescribe the appropriate amount of instruction. Studies by Tennyson and his associates (Park & Tennyson, 1980; Tennyson & Rothen, 1977) and Hansen et al. (1977) demonstrated the relative importance of these variables in predicting the appropriate amount of instruction. Subjects who received the amount of instruction selected based on the pretask measures (e.g., prior achievement, aptitude related to the task) needed less time to complete the task and showed a higher performance level on the posttest than subjects who received the same amount of instruction regardless of individual differences. In addition, some studies (Hansen et al., 1977; Ross & Morrison, 1988) indicated that only prior achievement among pretask measures (e.g., anxiety, locus of control) provides consistent and reliable information for prescribing the amount of instruction. However, subjects who received the amount of instruction selected based on both pretask measures and on-task measures needed less time and scored higher on tests than subjects who received the amount of instruction based on only pretask measures. The results of the response-sensitive strategies studied by Park and Tennyson (1980, 1986) suggest that the predictive power of the pretask measures, including prior knowledge, decreases, whereas that of on-task measures increases as the instruction progresses.

As reviewed above, a common characteristic of microadaptive instructional models is response sensitivity. For response-sensitive instruction, the diagnostic and prescriptive processes attempt to change the student's internal state of knowledge about the content being presented. Therefore, the optimal presentation of an instructional stimulus should be determined on the basis of the student's response pattern. Response-sensitive instruction has a long history of development, from Crowder's (1959) simple branching program to Atkinson's mathematical model of adaptive instruction. Until the late 1960s, technology was not readily available to implement the response-sensitive diagnostic and prescriptive procedures as a general practice outside the experimental laboratory (Hall, 1977). Although the development of computer

technology has made the implementation of this kind of adaptive procedures possible and allowed for further investigation of their instructional effects, as seen in the descriptions of microadaptive models, they have been limited mostly to simple tasks that can be easily analyzed for quantitative applications. However, the AI methodology has provided a powerful tool for overcoming the primary limitation of microadaptive instructional models, so the response-sensitive procedures can be utilized for more broad and complex domain areas.

25.5.4 Intelligent Tutoring Systems

Intelligent tutoring systems (ITSs) are adaptive instructional systems developed with the application of AI methods and techniques. ITSs are developed to resemble what actually occurs when student and teacher sit down one-on-one and attempt to teach and learn together (Shute & Psotka, 1995). As in any other instructional systems, ITSs have components representing the content to be taught; inherent teaching or instructional strategy, and mechanisms for understanding what the student does and does not know. In ITSs, these components are referred to as the problem-solving or expertise module, student-modeling module, and tutoring module. The expertise module evaluates the student's performance and generates instructional content during the instructional process. The student-modeling module assesses the student's current knowledge state and makes hypotheses about his or her conceptions and reasoning strategies employed to achieve the current state of knowledge. The tutorial module usually consists of a set of specifications for the selection of instructional materials the system should present and how and when they should be presented. AI methods for the representation of knowledge (e.g., production rules, semantic networks, and scripts frames) make it possible for the ITS to generate the knowledge to present the student based on his or her performance on the task rather than selecting the presentation according to the predetermined branching rules. Methods and techniques for natural language dialogues allow much more flexible interactions between the system and the student. The function for making inferences about the cause of the student's misconceptions and learning needs allows the ITS to make qualitative decisions about the learning diagnosis and instructional prescription, unlike the microadaptive model, in which the decision is based entirely on quantitative data.

Furthermore, ITS techniques provide a powerful tool for effectively capturing human learning and teaching processes. It has apparently contributed to a better understanding of cognitive processes involved in learning specific skills and knowledge. Some ITSs have not only demonstrated their effects for teaching specific domain contents but also provided research environments for investigating specific instructional strategies and tools for modeling human tutors and simulating human learning and cognition (Ritter & Koedinger, 1996; Seidel & Park, 1994). Recently, ITS technology has expanded to support metacognition (Aleven, Popescu, & Koedinger, 2001; White, Shimoda, & Frederiksen, 1999). Geometry Explanation Tutor is an example of an ITS supporting metacognition processes through dialogue. This system helps students learn through

self-explanation by analyzing student explanations of problem-solving steps, recognizing the type of omissions, and providing feedback. This kind of new pedagogical approach in ITSs is discussed more later.

However, there are criticisms that ITS developers have failed to incorporate many valuable learning principles and instructional strategies developed by instructional researchers and educators (Park, Perez, & Seidel, 1987). Cooperative efforts among experts in different domains, including learning/instruction and AI, are required to develop more powerful adaptive systems using ITS methods and techniques (Park & Seidel, 1989; Seidel, Park, & Perez, 1989). Theoretical issues about how to learn and teach with emerging technology, including AI, remain the most challenging problems.

25.5.5 Adaptive Hypermedia and Adaptive Web-Based Instruction

In the early 1990s, adaptive hypermedia systems inspired by ITSs were born (Beaumont, 1994; Brusilovsky, Schwarz, & Weber, 1996; Fischer, Mastaglio, Reeves, & Rieman, 1990; Gonschorek & Herzog, 1995; Kay & Kummerfeld, 1994; Pérez, Gutiérrez, & Lopistéguy, 1995). They fostered a new area of research combining adaptive instructional systems and hypermedia-based systems. Hypermedia-based systems allow learners to make their own path in learning. However, conventional hypermedia learning environments are a nonadaptive learning medium, independent from the individual user's responses or actions. They provide the same page content and the same set of links to all learners (Brusilovsky, 2000, 2001; Brusilovsky & Pesin, 1998). Also, learners choose the next task, which often leads them down a suboptimal path (Steinberg, 1991). These kinds of traditional hypermedia systems have been described as "user-neutral" because they do not consider the characteristics of the individual user (Brusilovsky & Vassileva, 1996). Duchastel (1992) criticized them as a nonpedagogical technology. Researchers tried to build adaptive and user model-based interfaces into hypermedia systems and thus developed adaptive hypermedia systems (Eklund & Sinclair, 2000). The goal of adaptive hypermedia is to improve the usability of hypermedia through the automatic adaptation of hypermedia applications to individual users (De Bra, 2000). For example, a student in an adaptive educational hypermedia system is given a presentation that is adapted specifically to his or her knowledge of the subject (De Bra & Calvi, 1998) and a suggested set of the most relevant links to pursue (Brusilovsky, Eklund, & Schwarz, 1998) rather than all users receiving the same information and same set of links. An adaptive electronic encyclopedia can trace user knowledge about different areas and provide personalized content (Milosavljevic, 1997). A virtual museum provides adaptive guided tours in the hyperspace (Oberlander, O'Donnell, Mellish, & Knott, 1998).

While most adaptive systems reviewed in the previous sections could not be developed without programming skills and were implemented in the laboratory settings, recent authoring tools allow nonprogrammers to develop adaptive hypermedia or adaptive Web-based instruction and implement it in real

instructional settings. Adaptive hypermedia or adaptive Web-based systems have been employed for educational systems, e-commerce applications such as adaptive performance support systems, on-line information systems such as electronic encyclopedias and information kiosks, and on-line help systems.

Since 1996, the field of adaptive hypermedia has grown rapidly (Brusilovsky, 2001), due in large part to the advent and rapid growth of the Web. The Web had a clear demand for adaptivity due to the great variety of users and served as a strong booster for this research area (Brusilovsky, 2000). The first International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems was held in Trento, Italy, in 2000 and developed into a series of regular conferences. Adaptive hypermedia and adaptive Web-based system research teams aim (a) to integrate information from heterogeneous sources into a unified interface, (b) to provide a filtering mechanism so that users see and interact with a view that is customized to their needs, (c) to deliver this information through a Web interface, and (d) to support the automatic creation and validation of links between related items to help with ongoing maintenance of the application (Gates, Lawhead, & Wilkins, 1998).

Because of its popularity and accessibility, the Web has become the choice of most adaptive educational hypermedia systems since 1996. Liberman's (1995) *Letizia* is one example of the earliest adaptive Web-based systems. *Letizia* is the system that assists users in web browsing by recommending links based on their previous browsing behaviors. Other early examples are ELM-ART (Brusilovsky, Schwarz, & Weber, 1996), InterBook (Brusilovsky, Eklund, & Schwarz, 1998), PT (Kay & Kummerfeld, 1994), and 2L670 (De Bra, 1996). These early systems have influenced more recent systems such as Medtech (Eliot, Neiman, & Lamar, 1997), AST (Specht, Weber, Heitmeyer, & Schöch, 1997), ADI (Schöch, Specht, & Weber, 1998), HysM (Kayama & Okamoto 1998), AHM (Pilar da Silva, Durm, Duval, & Olivie, 1998), MetaLinks (Murray, Condit, & Haugsjaa, 1998), CHEOPS (Negro, Scarano & Simari, 1998), RATH (Hockemeyer, Held, & Albert, 1998), TANGOW (Carro, Pulido, & Rodrigues, 1999), Arthur (Gilbert & Han, 1999), CAMELEON (Laroussi & Benahmed, 1998), KBS-Hyperbook (Henze, Naceur, Nejdil, & Wolpers 1999), AHA! (De Bra & Calvi, 1998), SKILL (Neumann & Zirvas, 1998), Multibook (Steinacker, Seeberg, Rechenberger, Fischer, & Steinmetz, 1998), ACE (Specht & Oppermann, 1998), and ADAPTS (Brusilovsky & Cooper, 2002).

25.5.5.1 Definition and Adaptation Methods. In a discussion at the 1997 Adaptive Hypertext and Hypermedia Discussion forum (from Eklund & Sinclair, 2000), adaptive hypermedia systems were defined as "all hypertext and hypermedia systems which reflect some features of the user in the user model and apply this model to adapt various visible and functional aspects of the system to the user." *Functional aspects* means those components of a system that may not visibly change in an adaptive system. For example, the "next" button will not change in appearance but it will take different users to different pages (Schwarz, Brusilovsky, & Weber, 1996). An adaptive hypermedia system should (a) be based on hypertext link principles (Park, 1983), (b) have a domain model, and (c) be capable of

modifying some visible or functional part of the system on the basis of information contained in the user model (Eklund & Sinclair 2000).

Adaptive hypermedia methods apply mainly to two distinctive areas of adaptation: adaptation of the content of the page, which is called content-level adaptation or adaptive presentation; and the behavior of the links, which is called link-level adaptation or adaptive navigation support.

The goal of adaptive presentation is to adapt the content of a hypermedia page to the learner's goals, knowledge, and other information stored in the user model (Brusilovsky, 2000). The techniques of adaptive presentation are (a) connecting new content to the existing knowledge of the students by providing comparative explanation and (b) presenting different variants for different levels of learners (De Bra, 2000).

The goal of adaptive navigation support is to help learners find their optimal paths in hyperspace by adapting the link presentation and functionality to the goals, knowledge, and other characteristics of individual learners (Brusilovsky, 2000). It is influenced by research on curriculum sequencing, which is one of the oldest methods for adaptive instruction (Brusilovsky, 2000; Brusilovsky & Pesin, 1998). Direct guidance, adaptive sorting, adaptive annotation, and link hiding, disabling, and removal are ways to provide adaptive links to individual learners (De Bra, 2000). ELM-ART is an example of direct guidance. It generates an additional dynamic link (called "next") connected to the next most relevant node to visit. However, a problem with direct guidance is the lack of user control. An example of the hiding-link technique is HYPERTUTOR. If a page is considered irrelevant because it is not related to the user's current goal (Brusilovsky & Pesin, 1994; Vassileva & Wasson, 1996) or presents material that the user is not yet prepared to understand (Brusilovsky & Pesin, 1994; Pérez et al., 1995), the system restricts the navigation space by hiding links. The advantage of hiding links is to protect users from the complexity of the unrestricted hyperspace and reduce their cognitive load in navigation. Adaptive annotation technology adds links with a comment that provides information about the current state of the nodes (Eklund & Sinclair, 2000). The goal of the annotation is to provide orientation and guidance. Annotation links can be provided in textual form or in the form of visual cues, for example, using different icons, colors, font sizes, or fonts (Eklund & Sinclair, 2000). Also, this user-dependent adaptive hypermedia system provides different users with different annotations. The method has been shown to be especially efficient in hypermedia-based adaptive instruction. (Brusilovsky & Pesin, 1995; Eklund & Brusilovsky, 1998). InterBook, ELM-ART, and AHM are examples of adaptive hypermedia systems applying the annotation technique. To provide links, annotation systems measure the user's knowledge in three main ways: (a) according to where the user has been (history based); (b) according to where the user has been and how those places are related (prerequisite based); and (c) according to a measure of what the user has shown to have understood (knowledge based) (Eklund & Sinclair, 2000).

Brusilovsky (2000) stated that "adaptive navigation support is an interface that can integrate the power of machine and human intelligence: a user is free to make a choice while still seeing an opinion of an intelligent system" (p. 3). In other words,

adaptive navigational support has the ability to decide what to present to the user, and at the same time, the user has choices to make.

25.5.5.2 User Modeling in Adaptive Hypermedia Systems. As in all adaptive systems, the user's goals or tasks, knowledge, background, and preferences are modeled and used for making adaptation decisions by adaptive hypermedia systems. In addition, recently the user's interests and individual traits have been studied in adaptive hypermedia systems. With the developed Web information retrieval technology, it became feasible to trace the user's long-term interests as well as the user's short-term search goal. This feature is used in various on-line information systems such as kiosks (Fink, Kobsa, & Nill, 1998), encyclopedias (Hirashima, Matsuda, Nomoto, & Toyoda, 1998), and museum guides (Not et al., 1998). In these systems, the user's interests serve as a basis for recommending relevant hypernodes.

The user's individual traits include personality, cognitive factors, and learning styles. Like the user's background, individual traits are stable features of a user. However, unlike the user's background, individual traits are not easy to extract. Researchers agree on the importance of modeling and using individual traits but disagree about which user characteristics can and should be used (Brusilovsky, 2001). Several systems have been developed for using learning styles in educational hypermedia (Carver, Howard, & Lavelle 1996; Gilbert & Han, 1999; Specht & Oppermann, 1998).

Adaptation to the user's environment is a new kind of adaptation fostered by Web-based systems (Brusilovsky, 2001). Since Web users are virtually everywhere and use different hardware, software, and platforms, adaptation to the user's environment has become an important issue.

25.5.5.3 Limitations of Adaptive Hypermedia Systems. The introduction of hypermedia and the Web has had a great impact on adaptive instructional systems. Recently, a number of authoring tools for developing Web-based adaptive courses have even been created. SmexWeb is one of these Web-based adaptive hypermedia training authoring tools (Albrecht, Koch, & Tiller, 2000). However, there are some limitations of adaptive hypermedia systems: They are not usually theoretically or empirically well founded. There was little empirical evidence for the effectiveness of adaptive hypermedia systems. Specht and Oppermann's study (1998) showed that neither link annotations nor incremental linkages in adaptive hypermedia system have significant separate effects. However, the composite of adaptive link annotations and incremental linking was found to produce superior student performance compared with to that of students receiving no annotations and static linking. The study also found that students with a good working knowledge of the domain to be learned performed best in the annotation group, whereas those with less knowledge appeared to prefer more direct guidance. Brusilovsky and Eklund (1998) found that adaptive link annotation was useful to the acquisition of knowledge for users who chose to follow the navigational advice. However, in a subsequent study (Eklund & Sinclair, 2000), link annotation was not found to influence user performance on the subject. The authors

concluded that the adaptive component was a very small part of the interface and insignificant in a practical sense. Also, De Bra pointed out that if prerequisite relationships in adaptive hypermedia systems are omitted by the user or just wrong, the user may be guided to pages that are not relevant or that the user cannot understand. Bad guidance is worse than no guidance (De Bra, 2000). Evaluating the learner's state of knowledge is the most critical factor for the successful implementation of the system.

25.6 APTITUDES, ON-TASK PERFORMANCE, AND RESPONSE-SENSITIVE ADAPTATION

As reviewed, microadaptive systems, including ITSs, demonstrate the power of on-task measures in adapting instruction to students' learning needs that are individually different and constantly changing, while ATI research has shown few consistent findings. Because of the theoretical implications, however, efforts to apply aptitude variables selectively in adaptive instruction continue. Integrating some aptitude variables in microadaptive systems has been suggested. For example, Park and Seidel (1989) recommended including several aptitude variables in the ITS student model and using them in the diagnostic and tutoring processes.

25.6.1 A Two-Level Model of Adaptive Instruction

To integrate the ATI approach in a microadaptive model, Tennyson and Christensen (1988; also see Tennyson & Park, 1987) have proposed a two-level model of adaptive instruction. This two-level model is based partially on the findings of their own research on adaptive instruction over two decades. First, this computer-based model allows the computer tutor to establish conditions of instruction based on learner aptitude variables (cognitive, affective, and memory structure) and context (information) structure. Second, the computer tutor provides moment-to-moment adjustment of instructional conditions by adapting the amount of information, example formats, display time, sequence of instruction, instructional advisement, and embedded refreshment and remediation. The microlevel adaptation takes place based on the student's on-task performance, and the procedure is response sensitive (Park & Tennyson, 1980). The amount of information to be presented and the time to display the information on the computer screen are determined through the continuous decision-making process of the Bayesian adaptive model based on on-task performance data. The selection and presentation of other instructional strategies (sequence of examples, advisement, embedded refreshment, and remediation) are determined based on the evaluation of the on-task performance. However, the response-sensitive procedure used in this microlevel adaptation has two major limitations, as discussed for the Bayesian adaptive instructional model: (a) problems associated with the quantification process in transforming the learning needs into the Bayesian probabilities and (b) the capability to handle only simple types of

learning tasks (e.g., concept and rule learning). For variables to be considered in the macroadaptive process, Tennyson and Christensen (1988) identified the types of learning objectives, instructional variables, and enhancement strategies for different types of memory structures (i.e., declarative knowledge, conceptual knowledge, and procedural knowledge) and cognitive processes (storage and retrieval). However, the procedure for integrating components of learning and instruction are not clearly demonstrated in their Minnesota Adaptive Instructional System.

25.6.2 On-Task Performance and Response-Sensitive Strategies

Studies reviewed for microadaptive models demonstrated the superior diagnostic power of on-task performance measures compared to pretask measures and the stronger effect of response-sensitive adaptation over ATI or nonadaptive instruction. These results indicate the relative importance of the response-sensitive strategy compared to ATI methods. The student's on-task performance or response to a given problem is the reflection of the integrated effect of all the variables, identifiable or unidentifiable, involved in the student's learning and response-generation process. As discussed earlier, a shortcoming of the ATI method is adapting instructional processes to one or two selected aptitude variables despite the fact that learning results from the integrated effects of many identifiable or unidentifiable aptitude variables and their interactions with the complex learning requirements of the given task. Some of the aptitude variables involved in the learning process may be stable in nature, whereas others are temporal. Identifying all of the aptitude variables and their interactions with the task-learning requirements is practically impossible.

Research evidence shows that some aptitude variables (e.g., prior knowledge, interest, intellectual ability) (Tobias, 1994; Whitener, 1989) are important predictors in selecting instructional treatments for individual students. However, some studies (Park & Tennyson, 1980, 1986) suggest that the predictive value of aptitude variables decreases as the learning process continues, because the involvement of other aptitude variables and their interactions may increase as learning occurs. For example, knowledge the student has acquired in the immediately preceding unit becomes the most important factor in learning the next unit, and the motivational level for learning the next unit may not be the same as that for learning the last unit. Thus, the general intellectual ability measured prior to instruction may not be as important in predicting the student's performance and learning requirements for the later stage or unit of the instruction as it was for the initial stage or unit.

In a summary of factor analytic studies of human abilities for learning, Fleishman and Bartlett (1969) provided evidence that the particular combinations of abilities contributing to performance change as the individual works on the task. Dunham, Guilford, and Hoepner (1968) also found that definite trends in ability factor loading can be seen as a function of stage of practice on the task. According to Fredrickson (1969), changes in the factorial composition of a task might be a function of the

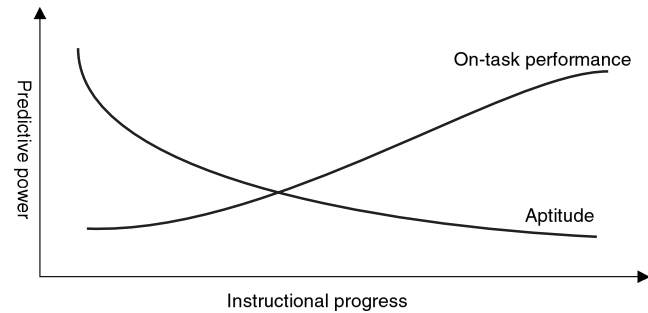


FIGURE 25.1. Predictive power of aptitudes and on-task performance.

student's employing cognitive strategies early in the learning task and changing the strategies later in the task. Because the behavior of the learner changes during the course of learning, including the learner's strategies, abilities that transfer and produce effects at one stage of learning may differ from those that are effective at other stages.

25.6.3 Diagnostic Power of Aptitudes and On-Task Performance

As discussed in the previous section, the change of aptitudes during the learning process suggests that the diagnostic power of premeasured aptitude variables for assessing the user's learning needs, including instructional treatments, decreases as learning continues. In contrast, the diagnostic power of on-task performance increases because it reflects the most up-to-date and integrated reflection of aptitude and other variables involved in the learning. Also, students' on-task performance in the initial stage of learning may not be as powerful as in the later stage of learning because, in the initial stage, they may not have sufficient understanding of the nature of the task or specific learning requirements in the task and their own ability related to the learning of the task. Therefore, during the initial stage of instruction, specific aptitude variables such as prior knowledge and general intellectual ability may be most useful in prescribing the best instructional treatment for the student. The decrease in the predictive power of premeasured aptitude variables and the increase in that of on-task performance are represented in Fig. 25.1.

25.6.4 Response-Sensitive Adaptation

Figure 25.1 suggests that an adaptive instructional system should be a two-stage approach: adaptation to the selected aptitude variable and response-sensitive adaptation. In the two-stage approach, the student will initially be assigned to the best instructional alternative for the aptitude measured prior to instruction, and then response-sensitive procedures will be applied as the student's response patterns emerge to reflect his or her knowledge or skills on the given task. A representative example of

this two-stage approach is the Bayesian adaptive instructional model. In this model, the student's initial learning needs are estimated from the student's performance on a pretest, and the estimate is continuously adjusted by reflecting the student's on-task performance (i.e., correct or incorrect response to the given question). As the process for estimating student learning needs continues in this Bayesian model, the pretest performance data become less important, and the most recent performance data become more important.

The response-sensitive procedure is particularly important because it can determine and use learning prescriptions with timeliness and accuracy during instruction. The focus of a response-sensitive approach is that the instruction should attempt to identify the psychological cause of the student's response and thereby lower the probability that similar mistakes will occur again rather than merely correcting each mistake. The effectiveness of a response-sensitive approach (e.g., Atkinson, 1968; Park & Tennyson, 1980, 1986) has been empirically supported. Also, some of the successful ITSs (e.g., SHERLOCK) diagnose the student's learning needs and generate instructional treatments based entirely on a student's response to the given specific problem, without an extensive student-modeling function.

Development of a response-sensitive system requires procedures for obtaining instant assessment of student knowledge or abilities and alternative methods for using those assessments to make instructional decisions. Also, the learning requirements of the given task, including the structural characteristics and difficulty level, should be assessed continuously by on-task analysis. Without considering the content structure, the student's response, reflecting his or her knowledge about the task, cannot be appropriately analyzed, and a reasonable instructional treatment cannot be prescribed. The importance of the content structure of the learning task was well illustrated by Scandura's (1973, 1977a, 1977b) structural analysis and Landa's (1970, 1976) algo-heuristics approaches.

To implement a response-sensitive strategy in determining the presentation sequence of examples in concept learning, Tennyson and Park (1980) recommended analyzing on-task error patterns from the student's response history and content and structural characteristics of the task. Many ITSs have incorporated functions to make inferences about the cause of a student misconception from the analysis of the student's response errors and the content structure and instantly to generate instructional treatment (i.e., knowledge) appropriate for the misconception.

25.6.5 On-Task Performance and Adaptive Learner Control

A curve similar to that for the instructional diagnostic power of aptitudes (Fig. 25.1) can be applied in predicting the effect of the learner-control approach. In the beginning stage of learning, the student's familiarity with the subject knowledge and its learning requirements will be relatively low, and the student will not be able to choose the best strategies for learning. However, as the process of instruction and learning continues and external or

self-assessment of the student's own ability is repeated, his or her familiarity with the subject and ability to learn it will increase. Thus, as the instruction progresses, the student will be able to make better decisions in selecting strategies for learning the subject. This argument is supported by research evidence that a strong effect of learner-control strategies is found mostly in relatively long-term studies (Seidel, Wagner, Rosenblatt, Hillelsohn, & Stelzer, 1978; Snow, 1980), whereas scattered effects are usually found in short-term experiments (Carrier, 1984; Ross & Rakow, 1981).

The speed, degree, and quality of obtaining self-regulatory ability in the learning process, however, will differ between students (Gallagher, 1994), because learning is an idiosyncratic process influenced by many identifiable and unidentifiable individual difference variables. Thus, an on-task adaptive learner control, which gradually gives learners the options for controlling the instructional process based on the progress of their on-task performance, should be better than non- or predetermined adaptive learner control, which gives the options without considering individual differences or is based on aptitudes measured prior to instruction. An on-task adaptive learner control will decide not only when is the best time to give the learner-control option but also which control options (e.g., selection of contents and learning activities) should be given based on the student's on-task performance. When the learner-control options are given adaptively, the concern that learner control may guide the student to put in less effort (Clark, 1984) would not be a serious matter.

25.7 INTERACTIVE COMMUNICATION IN ADAPTIVE INSTRUCTION

The response-sensitive strategies in CBI have been applied mostly to simple student-computer interactions such as multiple-choice, true-false, and short-answer types of questioning and responding processes. However, AI techniques for natural language dialogues have provided an opportunity to apply the response-sensitive strategy in a manner requiring much more in-depth communications between the student and the computer. For example, many ITSs have a function to understand and generate natural dialogues during the tutoring process. Although the AI method of handling natural languages is still limited and its development has been relatively slow, it is certain that future adaptive instructional systems, including ITSs, will have a more powerful function for handling response-sensitive strategies.

The development of a powerful response-sensitive instructional system using emerging technology, including AI, requires a communication model that depicts the process of interactions between the student and tutor. According to Wenger (1987), the development of an adaptive instructional system is the process of software engineering for constructing a knowledge communication system that causes and/or supports the acquisition of one's knowledge by someone else, via a restricted set of communication operations.

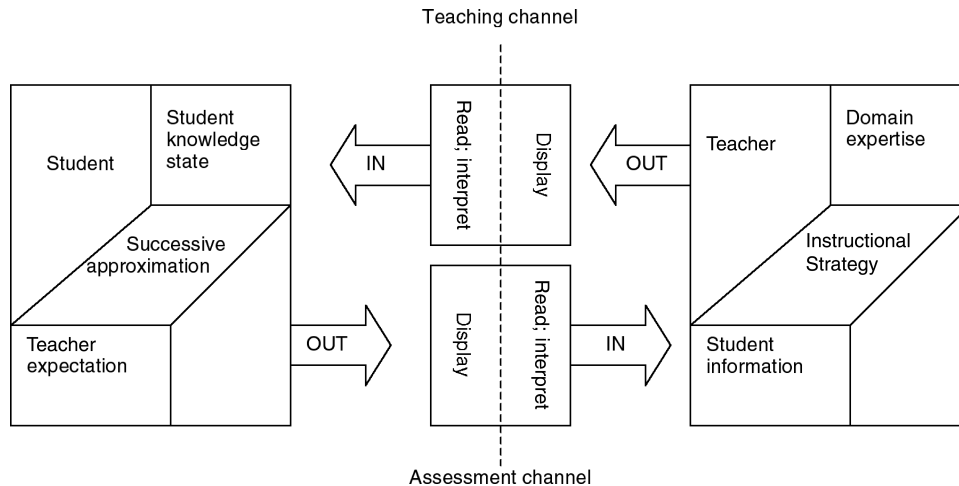


FIGURE 25.2. Process of instructional communication. From *Project IMPACT, Description of Learning and Prescription for Instruction* (Professional Paper 22–69), by R. J. Seidel, J. G. Compton, F. F. Kopstein, R. D. Rosenblatt, and S. See, 1969, Alexandria, VA: Human Resources Research Organization.

25.7.1 The Process of Instructional Communication

To develop a communication model for instruction, the process of instructional communication should first be understood. Seidel, Compton, Kopstein, Rosenblatt, and See (1969) divided instructional communication into teaching and assessment channels existing between the teacher and the student (Fig. 25.2 is adopted from Seidel et al. with modifications). Through the teaching channel, the teacher presents the student communication materials via the interface medium (e.g., computer display). The communication materials are generated from the selective integration of the teacher's domain knowledge expertise and teaching strategies based on information he or she has about the student. The student reads and interprets the communication materials based on the student's own current knowledge and the perceived teacher's expectation. The student's understanding and learning of the materials are communicated through his or her response or questions. The questions and responses by the student through the interface medium are read and interpreted by the teacher. Seidel et al. (1969; Seidel, 1971) called the communication process from the student to the teacher the assessment channel. Through this process, the teacher updates or modifies his or her information about the student and generates new communication materials based on the most up-to-date information. The student's knowledge successively approximates the state that the teacher plans to accomplish or expects.

The model of Seidel and his associates (1969) describes the general process of instruction. However, it does not explain how to assess the student's questions or responses and generate specific communication materials. Because specific combinations of questions and responses between the student and the teacher occurring in the teaching and assessment process are

mostly task specific, it is difficult to develop a general model for describing and guiding the process.

25.7.2 Diagnostic Questions and Instructional Explanations

Most student-system interactions in adaptive instruction consist of questions that the system asks to diagnose the student's learning needs and explanations that the system provides based on the student's learning needs. Many studies have been conducted to investigate classroom discourse patterns (see Cazden, 1986) and the effect of questioning (Farrar, 1986; Hamaker, 1986; Redfield & Rousseau, 1981). However, few principles or procedures for asking diagnostic questions in CBI or ITSs have been developed. Most diagnostic processes in CBI and ITSs take place from the analysis of the student's on-task performance. For assessing the student's knowledge state and diagnosing his or her misconceptions, two basic methods have been used in ITSs: (a) the overlay method for comparing student's current knowledge structure with the expert's and (b) the buggy method for identifying specific misconceptions from a precompiled list of possible misconceptions. In both methods, the primary source for identifying the student's knowledge structure or misconceptions is the student's on-task performance data.

From the analysis of interactions between graduate students and undergraduates they are tutoring in research methods, Graesser (1993) identified a five-step dialogue pattern to implement in an ITS: (a) tutor asks question; (b) student answers question; (c) tutor gives short feedback on answer quality; (d) tutor and student collaboratively improve on answer quality; and (e) tutor assesses student's understanding of the answer. According to Graesser's observation, tutor questions were

motivated primarily by curriculum scripts and the process of coaching students' idiosyncratic knowledge deficits. This five-step dialogue pattern suggests only a general nature of tutoring interactions rather than specific procedures for generating interactive questions and answers.

Collins and Stevens (1982, 1983) generated a set of inquiry techniques from analyses of teachers' interactive behaviors in a variety of domain areas. Nine of their most important strategies are (a) selecting positive and negative examples, (b) varying cases systematically, (c) selecting counterexamples, (d) forming hypotheses, (e) testing hypotheses, (f) considering alternative predictions, (g) entrapping students, (h) tracing consequences to a contradiction, and (i) questioning authority. Although these techniques are derived from the observation of classroom teachers' behaviors rather than experienced tutors', they provide valuable implications for producing diagnostic questions.

Brown and Palincsar (1982, 1989) emphasize expert scaffolding and Socratic dialogue techniques in their reciprocal teaching. Whereas expert scaffolding provides guidance for the tutor's involvement or provision of aids in the learning process, Socratic dialogue techniques suggest what kinds of questions should be asked to diagnose the student's learning needs. Five ploys are important in the diagnostic questions: (a) Systematic varied cases are presented to help the student focus on relevant facts, (b) counter examples and hypothetical cases are presented to question the legitimacy of the student's conclusions, (c) entrapment strategies are presented in questions to lure the student into making incorrect predictions or premature formulations of general rules based on faulty reasoning, (d) hypothesis identifications are forced by asking the student to specify his or her work hypotheses, and (e) hypothesis evaluations are forced by asking the student's prediction (Brown & Palincsar, 1989).

Leinhardt's (1989) work provides important implications for generating explanations for the student's misconceptions identified from the analysis of on-task performance or response. She identified two primary features in expert teachers' explanations: explicating the goal and objectives of the lessons and using parallel representations and their linkages. A model of explanation that she developed from the analysis of an expert tutor's explanations in teaching algebra subtraction problems shows that explanations are generated from various relations (e.g., pre-, co-, and prerequisite) between the instructional goal and content elements and the constraints for the use of the learned content.

As the preceding review suggests, efforts for generating principles of tutoring strategies (diagnosis and explanation) have continued, from observation of human tutoring activities (e.g., Berliner, 1991; Borke & Livingston, 1989; Leinhardt, 1989; Putnam, 1987) and from simulation and testing of tutoring processes in ITS environments (Ohlsson & Rees, 1991). However, specific principles and practical guidelines for generating questions and explanations in an on-task adaptive system have yet to be developed.

25.7.3 Generation of Tutoring Dialogues

Once the principles and patterns of tutoring interactions are defined, they should be implemented through interactions

(particularly dialogues) between the student and the system. However, the generation of specific rules for tutoring dialogues is an extremely difficult task. After having extensively studied human tutorial dialogues, Fox (1993) concluded that tutoring languages and communication are indeterminate, because a given linguistic item (including silence, face and body movement, and voice tones) is in principle open to an indefinite number of interpretations and reinterpretations. She argues that indeterminacy is a fundamental principle of interaction and that tutoring interactions should not be rule governed. Also, she says that tutoring dialogues should be contextualized, and the contextualization should be tailored to fit exactly the needs of the student at the moment. The difficulty of developing tutoring dialogues in an adaptive system suggests that the development of future adaptive systems should focus on the application of the advantageous features of computer technology for the improvement of the tutoring functions of the adaptive system rather than simulating human tutoring behaviors and activities. As discussed earlier, however, AI methods and techniques have provided a much more powerful tool for developing and implementing flexible interactions required in adaptive instruction than traditional programming methods used in developing ordinary CBI programs. Also, the development of computer technology, including AI, continuously provides opportunities to enrich our environment for instructional research, development, and implementation.

25.8 NEW PEDAGOGICAL APPROACHES IN ADAPTIVE INSTRUCTIONAL SYSTEMS

During the eighties and early nineties, adaptive CBI focused mainly on the acquisition of conceptual knowledge and procedural skills (see microadaptive models), the detection of predominant errors and misconceptions in specific domains, and the nature of dialogues between program (or tutor) and student (Andriessen and Sandberg, 1999). Ohlsson (1987, 1993) and others criticized ITSs and other computer-based interactive learning systems for their limited range and adaptability of teaching actions compared to rich tactics and strategies employed by human expert teachers. In the late nineties, researchers began to incorporate more complex pedagogical approaches such as metacognitive strategies, collaborative learning, constructivist learning, and motivational competence in adaptive instructional systems.

25.8.1 The Constructivist Approach

Constructivist learning theories emphasize active roles for learners in constructing their own knowledge through experiences in a learning context in which the target domain is integrated. The focus is on the learning process. The learners experience the learning context through the process rather than the acquisition of previously defined knowledge and construct their own knowledge based on their understanding. Meanwhile, most adaptive instructional systems have emphasized representation

of knowledge, inference of the learner's state of knowledge, and planning of instructional steps (Akhras & Self, 2000). Akhras and Self argued, "Alternative views of learning, such as constructivism, may similarly benefit from a system intelligence in which the mechanisms of knowledge representation, reasoning, and decision making originate from a formal interpretation of the values of that view of learning" (p. 345). Therefore, it is important to develop a different kind of system intelligence to support the alternative views and processes of learning. The constructivist intelligent system shifts the focus from a model of *what* is learned to a model of *how* knowledge is learned. Akhras and Self presented four main components of a constructivist intelligence system: context, activity, cognitive structure, and time extension. In the constructivist system, the context should be flexible enough to allow and accommodate different levels of learning experience within the context. Learning activities should be designed for learners to interact with the context and facilitate the process of knowledge construction through the interactions. The cognitive structure should be carefully designed so that learners' previously constructed knowledge influences the way they interpret new experiences. Also, learners should have chances to practice their previously developed knowledge to connect new knowledge over time (Akhras & Self, 2000).

Akhras and Self's approach was implemented in INCENSE (INtelligent Constructivist ENvironment for Software Engineering learning). INCENSE is capable of analyzing a time-extended process of interaction between a learner and a set of software-engineered situations and providing a learning situation based on the learner's needs. The goal of this system is to support further processes of learning experiences rather than the acquisition of target knowledge.

25.8.2 Vygotsky's Zone of Proximal Development and Contingent Teaching

According to Vygotsky (1978), "The zone of proximal development is those functions that have not yet matured, but would be possible to do under adult guidance or in collaboration with more capable peers" (p. 86). Based on Vygotsky's theory, providing immediate and appropriately challenging activities and contingent teaching based on learners' behavior is necessary for them to progress to the next level. He believed that minimal levels of guidance are best for learners. Recently, this theory has been deployed in several ways in CBI.

Compared to traditional adaptive instruction, one of the distinctions of this contingent teaching system is that there is no model of the learner. The learner's performance is local and situation constrained by contingencies in the learner's current activity. Since the tutor's actions and reactions occur in response to the learner's input, the theory promotes an "active" view of the learner and an account of learning as a collaborative and constructive process (D. Wood & H. Wood, 1996). The assessment of learners' prior knowledge with the task is critical to applying contingent teaching strategy to computer-based adaptive instruction. Thus, the contingent tutoring system generally provides two assessment methods: model tracing and knowledge tracing (du Boulay & Luckin, 2001). The purpose of model tracing is to keep track of all the student's actions as the problem

is solved and flag errors as they occur. It also adapts the help feedback according to the specific problem-solving context. The purpose of knowledge tracing is to choose the next appropriate problem so as to move the student through the curriculum in a timely but effective manner.

David Wood (2001) provided examples of tutoring systems based on Vygotsky's zone of proximal development (ZPD). ECOLAB is one. ECOLAB, which helps children aged 10-11 years learn about food chains and webs, provides appropriately challenging activities and the right quantity and quality of assistance. The learner model tracks both learners' capability and their potential to maintain the appropriate degree of collaborative assistance. ECOLAB ensures stretching learners beyond what they can achieve alone and then providing sufficient assistance to ensure that they do not fail.

Other examples are SHERLOCK (Karz & Lesgold, 1991; Karz, Lesgold, Egan, & Gordin, 1992), QUADRARIC (H. Wood & D. Wood, 1999), DATA (H. Wood, Wood, & Marston, 1998), and EXPLAIN (D. Wood, Shadbolt, Reichgelt, Wood, & Paskiewicz, 1992). In SHERLOCK, there is adjustment both to the nature of the activities undertaken by the user and to the language in which these activities are expressed. The working assumption is that more abstract language is harder and it moves from the concrete toward the abstract. QUADRARIC provides contingent, on-line help at the learner's request. The tutor continually monitors and logs learner activity and, in response to requests for help, exploits principles of instructional contingency to determine what help to provide. DATA was designed to undertake on-line assessment prior to tutoring. Based on on-line assessment, all learners are offered tutoring in the classes of problems with which they have shown evidence of error during the assessment. EXPLAIN (Experiments in Planning and Instruction) challenges learners to master tasks with presentation of manageable problems. This involves tutorial decisions about what challenges to set for the learner, if and when to intervene to support them as they attempt given tasks, and how much help to provide if they appear to need support.

However, these contingent-based learning systems have limitations. Hobsbaum, Peters, and Syla (1996) argue that the specific goals for tutorial action often arise out of the process of tutorial interactions and the system does not appear to follow a prearranged program. Learners often develop their own problem-solving strategies that differ from those taught. A competent tutor should be able to provide help or guidance contingent on any learner's conceptions and inputs. However, these systems cannot reliably diagnose such complex idiosyncratic conceptions and hence have limitation to provide useful guidance contingent on such conceptions.

25.8.3 Adaptation to Motivational State

Some new adaptive instructional systems take account of students' motivational factors. Their notion suggests that a comprehensive instructional plan should consist of a "traditional" instructional plan combined with a "motivational" plan. Wasson (1990) proposed the division of instructional planning into two streams: (a) content planning for selecting the topic to teach next and (b) delivery planning for determining how to teach

the selected topic. Motivational components should be considered while designing delivery planning.

For example, in new systems, researchers try to incorporate gaze, gesture, nonverbal feedback, and conversational signals to detect and increase students' motivation. COSMO and MORE are examples of adaptive systems that focus on motivational components. COSMO supports a pedagogical agent that can adapt its facial expression, its tone of voice, its gestures, and the structure of its utterances to indicate its own affective state and to add affective force during its interactions with learners (du Boulay & Luckin, 2001). MORE detects the student's motivational state and reacts to motivate the distracted, less confident, or disoriented student or to help sustain the disposition of the already motivated student (du Boulay & Luckin, 2001).

25.8.4 Teaching Metacognitive Ability

Metacognitive skill is students' understanding of their own cognitive processes. Educational psychologists including Dewey, Piaget, and Vygotsky argued that understanding and control of one's own cognitive processes play a key role in learning. Carroll and McKendree (1987) criticized the fact that most tutoring systems do not promote students' metacognitive thinking skills. White et al. (1999) considered that metacognitive processes are easily understood and observed in a multiagent social system, which integrates cognitive and social aspects of cognition within a social framework. Based on this conceptual framework, they developed the SCI-WISE program. It houses a community of software agents, such as an Inventor, an Analyzer, and a Collaborator. The agents provide strategic advice and guidance to learners as they undertake research projects and as they reflect on and revise their inquiry. Therefore, students express their metacognitive ideas as they undertake complex sociocognitive practices. Through this exercise, students will develop explicit theories of the social and cognitive processes required for collaborative inquiry and reflective learning (White et al., 1999).

Another example focusing on improving metacognitive skills is the Geometry Explanation Tutor program, developed by Alevin et al. (2001). They argue that self-explanation is an effective metacognitive strategy. Explaining examples or problem-solving steps helps students learn with greater understanding (Chi, Bassok, Lewis, Reimann, & Glaser, 1989). Originally, Geometry Explanation Tutor was created by adding dialogue capabilities to the PACT Geometry tutor. The current Geometry Explanation Tutor engages students in a restricted form of dialogue to help them state general explanations that justify problem-solving steps. The tutor is able to respond to the types of incomplete statements in the student's explanations. Although its range of dialogue strategies is currently very limited, it promotes students' greater understanding of geometry.

25.8.5 Collaborative Learning

Adaptive CBI systems including ITs are no longer viewed as stand-alone but as embedded in a larger environment in which students are offered additional support in the learning process (Andriessen & Sandberg, 1999). One new pedagogical approach

of adaptive instructional systems is to support collaborative learning activities. Effective collaboration with peers is a powerful learning experience and studies have proved its value (Piaget, 1977; Brown & Palinscar, 1989; Doise, Mugny, & Perret-Clermont, 1975). However, placing students in a group and assigning a group task does not guarantee that they will have a valuable learning experience (Soller, 2001). It is necessary for teachers (tutors) to provide effective strategies with students to optimize collaborative learning. Through his Intelligent Collaborative system, Soller (2001) identified five characteristics of effective collaborative learning behaviors: participation, social grounding, performance analysis, group processing and application of active learning conversation skills, and promotive interaction. Based on these five characteristics, he listed components of an intelligent assistance module in a collaborative learning system, which include a collaborative learning skill coach, an instructional planner, a student or group model, a learning companion, and a personal learning assistant.

Erkens (1997) identified four uses of adaptive systems for collaborate learning: computer-based collaborative tasks (CBCT), cooperative tools (CT), intelligent cooperative systems (ICS), and computer-supported collaborative learning (CSCL).

1. CBCT: Group learning or group activity is the basic method to organize collaborative learning. The system presents a task environment in which students work with a team, and sometimes, the system supports the collaboration via intelligent coaching. SHERLOCK (Karz & Lesgold, 1993) and Envisioning Machines (Roschell & Teasley, 1995) are examples.
2. CT: The system is a partner that may take over some of the burden of lower-order tasks while students work with higher-order activities. Writing Partner (Salomon, 1993), CSILE, and Case-based Reasoning Tool are examples.
3. ICS: The system functions as an intelligent cooperative partner (e.g., DSA), a colearner (e.g., People Power), or a learning companion (e.g., Integration-Kid).
4. CSCL: The system serves as the communication interface such as a chat tool or discussion forum, which allows students to involve collaboration. The systems in this category provide the least adaptability to learners. Owing to the development of Internet-based technology (Web), however, this kind of system has been improving rapidly with the strong adaptive capability.

Although these systems are still in the early developmental stage, their contribution to the adaptive instructional system field cannot be ignored; they not only facilitate group activities, but also help educators and researchers gain further understanding of group interaction and determine how to support collaborative learning better.

25.9 A MODEL OF ADAPTIVE INSTRUCTIONAL SYSTEMS

In the preceding section, we emphasized the importance of on-task performance or a response-sensitive approach in the development of adaptive instructional systems. However, a complete adaptive system should have the capability to update

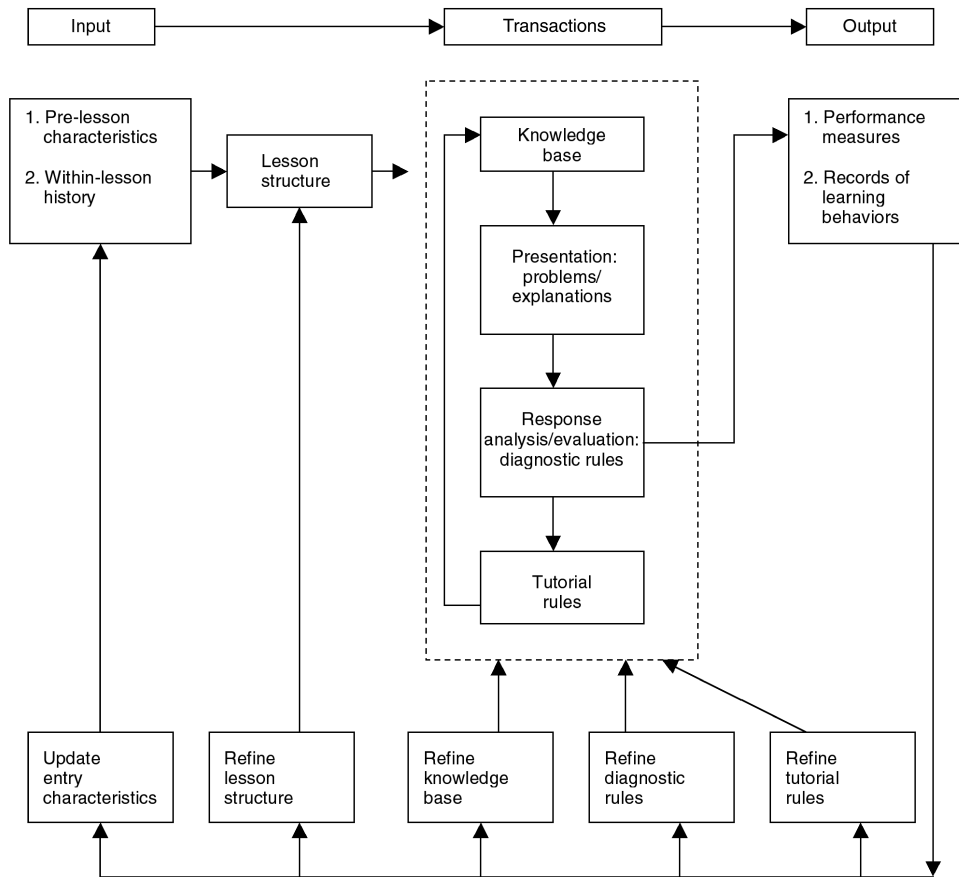


FIGURE 25.3. A model of adaptive instruction (Park et al., 1987). Originally from *Theories and Strategies Related to Measurement in Individualized Instruction* (Professional Paper 2-72), by R. J. Seidel, 1971, Alexandria, VA: Human Resources Research Organization.

continuously every component in the instructional system based on the student's on-task performance and the interactions between the student and the system. However, almost all adaptive instructional systems, including ITSS, have been developed with an emphasis on a few specific aspects or functions of instruction. Therefore, we present a conceptual model for developing a complete adaptive instructional system (Fig. 25.3). This model is adopted from the work of Seidel and his associates (Seidel, 1971), with consideration of recent developments in learning and instructional psychology and computer technology (Park et al., 1987).

This model does not provide specific procedures or technical guidelines for developing an adaptive system. However, we think that the cybernetic metasystem approach used in the model is generalizable as a guide for developing the more effective and efficient control process required in adaptive instructional systems. The model illustrates what components an adaptive system should have and how those components should be interrelated in an instructional process. Also, the model shows what specific self-improving or updating capabilities the system may need to have.

As Fig. 25.3 shows, this model divides the instructional process into three stages: input, transactions, and output. The input stage basically consists of the analysis of the student's entry characteristics. The student's entry characteristics include not only his or her within-lesson history (e.g., response history) but also prelesson characteristics. The prelesson characteristics may include information about the student's aptitudes and other variables influencing his or her learning. As discussed earlier, the aptitude variables measured prior to instruction will be useful for the beginning stage of instruction but will become less important as the student's on-task performance history is accumulated. Thus, the within-lesson history should be continuously updated using information from the evaluation of the performance (i.e., output measures).

The transaction stage consists of the interactions between the student and the system. In the beginning stage of the instruction, the system will select problems and explanations to present based on the student's entry characteristics, mainly the premeasured aptitudes. Then the system will evaluate the student's responses (or any other student input such as questions or comments) to the given problem or task. The response

evaluation provides information for diagnosing the student's specific learning needs and for assessing overall performance level on the task. The learning needs will be inferred according to diagnostic rules in the system. Finally, the system will select new display presentations and questions for the student according to the tutorial rules. The tutorial rules should be developed in consideration of different learning and instructional theories (e.g., see Snelbecker, 1974; Reigeluth, 1983), research findings (e.g., see Gallanher, 1994; Weinstein & Mayer, 1986), expert heuristics (Jonassen, 1988), and response-sensitive strategies discussed earlier in this chapter.

The output stage consists mainly of performance evaluation. The performance evaluation may include not only the student's overall achievement level on a given task and specific performance on the subtasks but also the analysis of complete learning behaviors related to the task and subtasks. According to the performance evaluation and analysis, the instructional components will be modified or updated. The instructional components to be updated may include contents in the knowledge base (including questions and explanations), instructional strategies, diagnostic and tutorial rules, the lesson structure, and entry characteristics. If the system does not have the capability to modify or update some of the instructional components automatically, a human monitor may be required to perform that task.

25.10 CONCLUSION

Adaptive instruction has a long history (Reiser, 1987). However, systematic efforts aimed at developing adaptive instructional systems were not made until the early 1900s. Efforts to develop adaptive instructional systems have taken different approaches: macroadaptive, ATI, and microadaptive. Macroadaptive systems have been developed to provide more individualized instruction on the basis of the student's basic learning needs and abilities determined prior to instruction. The ATI approach is to adapt instructional methods, procedures, or strategies to the student's specific aptitude information. Microadaptive systems have been developed to diagnose the student's learning needs and provide optimal instructional treatments during the instructional transaction process.

Some macro-adaptive instructional systems seemed to be positioned as alternative educational systems because of their demonstrated effectiveness. However, most macrosystems were discontinued without much success because of the difficulty associated with their development and implementation, including curriculum development, teacher training, resource limitation, and organizational resistance. Numerous studies have been conducted to investigate ATI methods and strategies because of ATI's theoretically appealing and practical application possibilities. However, the results are not consistent and have provided little impetus for developing adaptive instructional systems.

Using computer technology, a number of micro-adaptive instructional systems have been developed. However, their applications had been mostly in laboratory environments because of the limitation of their functional capability to handle the

complex transaction processes involved in the learning of various types of tasks by many different students. In the last decade, with the advent of the Web and adaptive hypermedia systems, their applications have moved out of the laboratory and into classrooms and workplaces. However, empirical evidence of the effectiveness of the new systems is very limited.

Another reason for the limited success of adaptive instructional systems is that unverified theoretical assumptions were used for their development. Particularly, ATI, including achievement and treatment interactions, has been used as the theoretical basis for many studies. However, the variability of ATI research findings suggests that the theoretical assumptions used may not be valid, and the development of a complete taxonomy of all likely aptitudes and instructional variables may not be possible. Even if it is possible to develop such a taxonomy, its instructional value will be limited because learning will be influenced by many variables, including aptitudes. Also, the instructional value of aptitude variables measured prior to instruction decreases as the instruction progresses. In the meantime, students' on-task performance (i.e., response to the given problem or task) becomes more important for diagnosing their learning needs (see Fig. 25.1) because on-task performance is the integrated reflection of many verifiable and unverifiable variables involved in learning.

Therefore, we propose an on-task performance and treatment interaction approach. In this approach, response-sensitive methods will be used as the primary strategy. Many studies (e.g., Atkinson, 1974; Park & Tennyson, 1980, 1986) have demonstrated the effects of response-sensitive strategies. However, application of the response-sensitive strategy has been limited to simple tasks such as vocabulary acquisition and concept learning because of the technical limitations in handling the complex interactions involved in the learning and teaching of more sophisticated tasks such as problem solving. However, ITSs created in the last two decades have demonstrated that technical methods and tools are now available for the development of more sophisticated response-sensitive systems. Unfortunately, this technical development has not contributed significantly to an intellectual breakthrough in the field of learning and instruction. Thus, no principles or systematic guidelines for developing questions and explanations necessary in the response-sensitive strategy have been developed. In this chapter, we have reviewed several studies that provide some valuable suggestions for the development of response-sensitive strategies, including asking diagnostic questions and providing explanations (Collins & Stevens, 1983; Brown & Palincsar, 1989; Leinhardt, 1983). Further research on asking diagnostic questions and providing explanations is needed for the development of response-sensitive adaptive systems.

Since response-sensitive diagnostic and prescriptive processes should be developed on the basis of many types of information available in the system, we propose to use a complete model of adaptive instructional systems described by Park et al. (1987). This model consists of input, transactions, and output stages, and components directly required to implement the response-sensitive strategy are in the transaction stage of instruction. To develop an adaptive instructional system using this model will require a multidisciplinary approach because it

will require expertise from different domain areas such as learning psychology, cognitive science or knowledge engineering, and instructional technology (Park & Seidel, 1989). However, with the current technology and our knowledge of learning and instruction, the development of a complete adaptive instructional system like the one shown in Fig. 25.3 may not be possible in the immediate future. It is expected that cognitive scientists

will further improve the capabilities of current AI technology such as natural language dialogues and inferencing processes for capturing the human reasoning and cognitive process. In the meantime, the continuous accumulation of research findings in learning and instruction will make a significant contribution to instructional researchers' and developers' efforts to create more powerful adaptive instructional systems.

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