22. ADAPTIVE INSTRUCTIONAL SYSTEMS

Ok-choon Park
U.S. ARMY RESEARCH INSTITUTE

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* (Corno & 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 interchangeably used with *individualized instruction* in the literature (Wang & Lindvall, 1984; Reiser, 1987). However, they are different depending on 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, since instruction will be most powerful when it is adapted to unique needs of each individual. It can be easily 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 admonition for adapting instruction to individual student's needs has been documented by many researchers (e.g., Corno & 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 (Corno & 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, 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 (1902/1964). Nine years later, Thorndike (1911) argued for a specialization of instruction that acknowledged differences 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 (see Reiser, 1987, for early systems).

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, to realize 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) selectively to review systematic efforts for establishing and implementing adaptive instruction, (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 an adaptive instruction.

22.1 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, delivery systems, etc. Most adaptive instructional systems developed as alternatives to the traditional lock-step group instruction in school environments have taken this approach. In this macro-approach, instructional alternatives are mostly selected 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. Since 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. Since this micro-approach is designed to guide the student's ongoing learning process throughout the instruction, the diagnosis and prescription are often continuously performed from the 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 micro-adaptive 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 micro-adaptive instructional systems more efficiently than ever before. Thus, in this chapter micro-adaptive instructional systems and the related issues are reviewed and discussed more thoroughly than macro-adaptive systems and ATI approaches.

22.2 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 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 better accommodate different student abilities. As examples, 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 her or his own pace. The notion of mastery learning was also fostered in Dalton and Winnetka plans (Reiser, 1987).

Since macro-adaptive 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 (Corno & 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 macro-adaptive instructional systems developed in the 1960s are briefly reviewed below.

22.2.1 Keller Plan

In 1963, Keller and his associates (Keller, 1968, 1974) at Columbia University developed a macro-adaptive 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 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.

22.2.2 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 audio-tutorial approach was a tutorial-like instruction using audiotapes, along with other media like texts, slides, models, etc. This approach was effectively used for teaching college science courses (Postlethwait, 1981).

22.2.3 PLAN

In 1967, Flanagan and his associates (Flanagan, Shanner, Brudner & 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 the mastery before advancing to the next unit for other objective(s). In the early 1970s, more than 100 elementary schools participated in this program.

22.2.4 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 her or his 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.

22.2.5 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 academic-ability 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 necessary guidance for each student, and selects alternative instructional materials (e.g., text, audiovisuals, group activities, etc.) 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.

22.2.6 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 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.

22.2.7 ALEM

The LRDC extended IPI with more various 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 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 (Corno & 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.

22.2.8 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, lesson, course, and 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. The PLM 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, the PLM assigns a learning activity or activities for the student. After studying the learning activities, the student is required to take the test again. When the student demonstrates the mastery of all objectives in the module, the student is allowed to move to the next module. Depending on the instructor 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, the PLM provides several other features important in adapting instruction to the student's needs and ability: (a) the instructor is 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) frequently, more than one learning activity is associated with an instructional objective, and the student has the option to choose which activity or activities to study; and (d) since most learning activities associated with the PLM are instructor-free, the student can choose the time to study it and progress at his or her own pace.

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

Ross and Morrison (1988) developed a macro-adaptive system combining some of the basic functions of CMI (e.g., prescription of instruction) and some of the features of micro-adaptive models (e.g., prediction of student learning needs). Unlike the PLM, this system was designed primarily for providing adaptive instruction rather than managing the instructional process. However, the student's learning needs are diagnosed only from preinstructional data, and a new instructional prescription cannot be generated until the next unit of instruction begins. This system consisted of three basic steps: First, variables for predicting the student's performance on the task are selected (e.g., measures of prior knowledge, reading comprehension, locus of control, and anxiety). Second, a predictive equation is developed using multiple regression analysis. Third, 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 micro-adaptive model (trajectory/multiple regression approach) described in a later section.

The macro-adaptive instructional programs described above are representative examples that have been instantiated and 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 widely different among teachers. Thus, several different models have been proposed to examine analytically the different levels and methods of adaptive instruction and to provide guidance for developing adaptive instructional programs.

22.3 MACRO-ADAPTIVE INSTRUCTIONAL MODELS

22.3.1 A Taxonomy of Macro-Adaptive Instruction

Corno 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. Corno and Snow distinguished two different 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: (a) intellectual abilities and prior achievement, (b) cognitive and learning styles, and (c) academic motivation and related personality characteristics. (For in-depth discussions about aptitudes in relation to adaptive instruction, see Federico, 1980; Cronbach & Snow, 1977; Snow, 1986; Snow & Swanson, 1992; Tobias, 1987.) Corno and Snow categorized instructional mediation into four types, from the least intrusive form of mediation to the most intrusive one: (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 Corno 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 the 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.

22.3.2 Macro-Adaptive Instructional Models

While Corno 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 the student does not have appropriate initial competence to achieve the objective with the given activity, he or she is designated as a poor learner and is dropped out. Only students who demonstrate the appropriate initial state of competence are allowed to participate in the instructional activity. If the student does not demonstrate the achievement of the objective after the activity, the student is allowed to repeat the same activity or is 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 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 the student does not have initial competence appropriate for any of the alternative activities, she or he is designated as 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 learning; 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.

22.3.3 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, while another learner of differing characteristics would receive an entirely different form of instruction. This strategy has been termed *aptitude-treatment interaction* (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 defined *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): (1) cognitive aptitudes, and (2) conative and affective aptitudes. Cognitive aptitudes include: (a) intellectual ability constructs mostly consisting 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 different 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.

22.3.4 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; Gallangher, 1994; Snow, 1986; Snow & Swanson, 1992; Tobias, 1983, 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 below.

22.3.4.1. 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, Corno 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.

22.3.4.2. 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 different 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, tolerance of unrealistic experiences, etc.), 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: (a) self-motivated and influenced by internal reinforcement, and (b) better at analyzing features and dimensions of information and for conceptually restructuring it. In contrast, field-dependent persons are more likely to be: (a) concerned with what others think and affected by external reinforcement, and (b) 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: (a) take more time to examine problem situations and make fewer errors in their performance, (b) exhibit more anxiety over making mistakes on intellectual tasks, and (c) separate patterns into different features. In contrast, impulsive persons have a tendency to: (a) show greater concern about appearing incompetent due to slow responses and take less time examining problem situations, and (b) 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).

22.3.4.3. Learning Styles. Efforts for matching instructional presentation and materials with the student's preferences and needs have produced a number of different learning styles (Schmeck, 1988). For example, Pask (1976, 1988) identified two learning styles: (a) a holist, who prefers 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 (b) a serialist, who prefers 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 different learning styles within each category. The student's preference in environmental stimuli can be quiet or noisy 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), and more or less persistent, and more or less responsible. For sociological stimuli, students may prefer learning alone, with peers, with adults, or through 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 above provides some practical implications for designing adaptive instruction. However, there is not yet sufficient empirical evidence to support the value of learning styles, and no reliable methods for assessing the different learning styles developed.

22.3.4.4. 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. Since 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 showed 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).

22.3.4.5. Anxiety. Many studies showed 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 a 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.

22.3.4.6. Achievement Motivation. Motivation is an associative network of affectively toned personality characteristics such as self-perceived competence, locus of control, anxiety, etc. (McClelland, 1965). Thus, understanding and incorporating the interactive roles of motivation with cognitive process variables during instruction is important. However, little research evidence is available for understanding the interactions between the affective and 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. Nicholla, Jagacinski, and Miller (1986) 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 primarily motivated by hope for success. The meaning-oriented students are more likely to adopt a holist learning strategy that requires deep cognitive processing, while the reproduction-oriented students tend to adopt a serialist strategy that requires relatively shallow cognitive processing (Schmeck, 1988). The 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 other 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.

Recently, 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.

22.3.4.7. Self-Efficacy. Self-efficacy influences people's intellectual and social behaviors, including academic achievement (Bandura, 1982). Since 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 variables discussed above, many other individual difference variables (e.g., locus of control, cognitive development stages, cerebral activities and topological localization of brain hemisphere, personality variables, etc.) have been studied in relation to learning and instruction. Few studies, however, provided feasible suggestions for adapting instruction to individual differences in these variables.

22.3.5 A Taxonomy of Instructional Strategies

Although numerous learning 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 22-1) 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/instructional processes and do not provide direct or indirect suggestions for selecting instructional strategies in ATI research or adaptive instructional development.

22.3.6 Limitations of Aptitude-Treatment Interactions

In the 3 decades since Cronbach (1957) made his proposal, relatively few studies have found consistent results to support the paradigm and made little contribution to either instructional theory or practice. As several reviews of ATI research (Berlinger & 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. The limitations are:

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.

22.3.7 Achievement-Treatment Interactions

To reduce some of the difficulties in the ATI approach, Tobias (1976) proposed an alternative model, achievement-treatment interactions (see 33.9.1). While 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

TABLE 22-1. A TAXONOMY OF INSTRUCTIONAL STRATEGIES (PARK, 1984; SEIDEL, PARK & PEREZ, 1988). (THE LISTING OF INSTRUCTIONAL STRATEGIES IN THIS TABLE IS NOT EXHAUSTIVE, AND THE CLASSIFICATIONS ARE ARBITRARILY MADE.)

1. Preinstructional Strategies

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, etc. vs. subjective: short answer, essay, etc.)
   Order of test item presentation (e.g., random, sequence, response-sensitive, etc.)
   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)

2. Knowledge Presentation Strategies

1. **Types of knowledge presentation**
   Generality (e.g., definition, rules, principles, etc.)
   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 knowledge acquisition**
   Mnemonic
   Metaphors and analogies
   Attribute isolations (e.g., coloring, underlining, etc.)
   Verbal articulation
   Observation and emulation

3. Interaction Strategies

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, etc.)
   Time of feedback (e.g., immediate vs. delayed feedback)
   Type of feedback (e.g., cognitive/informative feedback vs. psychological reinforcing)

4. 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

5. 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, etc. vs. subjective: short answer, essay, etc.)
   Order of test item presentation (e.g., random, sequence, response-sensitive, etc.)
   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)

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 upon 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 might be lost by discounting possible contribution of factors such as intellectual ability, cognitive style, anxiety, motivation, etc.

22.3.8 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 that are relatively molar processes, such as mental tactics (Derry & Murphy, 1986), and deployed under student's volitional control; and (b) microprocesses that 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, 1988) conducted a series of experiments in rereading comprehension using 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, rereading with external support, etc.). 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 are meaningfully related to student characteristics such as anxiety, domain-specific knowledge, or 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.

22.3.9 Learner Control

An alternative approach to adaptive instruction is learner control (see 33.2) that 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 (see 33.2) The results have provided some important implications for developing adaptive systems: (a) Individual differences play an important role in the success of learner control strategy; (b) some learning activities performed during the instruction are closely related to the effectiveness of learner control; and (c) 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 or 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 (see 33.5.4), 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.

22.3.10 An Eight-Step Model for Designing ATI Courseware

As reviewed above, 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.

In spite of 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 computer-based instructional (CBI) courseware. The eight steps are: (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 (Gagné & Briggs, 1979; Dick & Carey, 1985). This model proposes to identify specific learner characteristics of the individual student 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. They are (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, anxiety, etc. (see p. 205 in Carrier & Jonassen, 1988). For instructional adaptation, they recommended several types of instructional matches: (a) remedial, (b) capitalization/preferential, (c) compensatory, and (d) 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 that of 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.

22.4 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 for finding 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 could 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 (ITS) (see 19.3 to 19.5).

22.4.1 Programmed Instruction

Skinner has generally been considered the pioneer of programmed instruction (see 2.3.4). However, 3 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 learning 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 (see 2.3.4.2). 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 (see 2.3.4.1). 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 (see 2.3.4.2). 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 her or his 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 Key-board 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 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 which included instruction of conceptual as well as perceptual motor tasks.

As described above, most of 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.

22.4.2 Micro-Adaptive Instructional Models

Using computer technology, a number of micro-adaptive 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, while the early programmed instruction was primarily based on intuition and its adaptation was primitive. Unlike macro-adaptive models, the micro-adaptive 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 micro-adaptive model is its dynamic nature as contrasted with a macro-adaptive model. A typical micro-adaptive model includes more variables related to instruction than a macro-adaptive model or programmed instruction. It thus provides a better control process than a macro-adaptive model or programmed instruction in responding to the student's performance in reference to type of content and behavior required in a learning task (Merrill & Boutwell, 1973).

As described by Suppes, Fletcher, and Zanottie (1976), most micro-adaptive models use a quantitative representation and trajectory methodology. The most important feature of a micro-adaptive 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 micro-adaptive 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.

22.4.2.1. 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) deducted three strategies for prescribing the most effective instructional sequence for a few special subjects, like 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). The dynamic programming technique is a method for finding an optimal strategy by systematically varying the number of learning stages and obtaining an expression that gives the return for a process with n stages as a function of the return for a process with $n - 1$ stages. The operational function in a deterministic process of the all-or-none strategy is $Wn = T(Wn - 1, dn - 1)$, where W is the student's state in learning, n is the stage, and d is the decision (Groen & Atkinson, 1966). In this strategy, the items should be presented at well-spaced intervals, because it is not effective under the condition of massed presentation (Dear, Silberman, Estavan & Atkinson, 1967).

This all-or-none model does not depend on the values of its parameters. In other words, such parameters as the probability of changing an item in the unlearned state to the learned state with a presentation of the item, probability of making a correct response by guessing, and the initial error probability are constant throughout all stages because of the assumption that items and students are homogeneous.

On the basis of Norman's (1964) work, Atkinson and Paulson (1972) proposed the random-trial incremental model, a compromise between the linear and 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). The initial parameter of a subject-item (π_{ij}) is estimated with an analysis of variance model: $E(\pi_{ij}) = m = a_i + d_j$, where m is the mean, a_i is the probability of student i, and d_j is the difficulty of item j. Because this equation cannot generate the probabilities of the parameters ($0 < \pi_{ij} < 1$), it is transformed in a logistic equation through an algebraic operation and a logarithmic procedure (see Atkinson & Paulson, 1972). The logistic equation is $logit\ \pi_{ij} = \mu + A_i + D_j$, where μ is the mean, A_i is the ability of student i applied across all items, and D_j is the difficulty of item j applied across all students. This logistic equation reduces the number of parameters for N items $\times$ S subjects to $N + S$ parameters. The subject and item effects (A_i and D_j are estimated by standard analysis of variance procedures. Using the estimated student and item effects, the logit μ_{ij} is transformed back to obtain the final estimates of the original student-item parameter.

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, since 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. The utility function, $U_a(k, h)$, specifies the immediate value accrued if alternative a is presented to a student with response history (h), and k is the response elicited. The terminal utility function is $U_o(h)$, which describes the utility associated with terminating the instruction for a student with a past history h. 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.

Recently, 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 can be obtained about how the variables in the model interact, 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 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 are 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.

22.4.2.2. 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 (Supppes, Fletcher & Zanotti, 1976). Using this theoretical view, Hansen, Ross, and Rakow (1977; Ross & Rakow, 1982; Ross & Morrison, 1988) developed an adaptive model that reflects both group and individual indices and matches them to appropriate changes both for 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.

The procedures Hansen et al. used to develop an adaptive system using the trajectory model are as follows:

(a) Learning and test materials were prepared (for example, the instructional unit consisted of 10 basic algebra rules) and the predictive input database was obtained from two measures of personality variables (locus of control and trait anxiety), one measure of general aptitude related to the task (math and verbal), and one measure of a subject familiarity (pretest). Upon completion of the pretest, the subject was given the programmed manual and task instructions. After working through the manual, the student took the posttest, which was matched to the pretest in the number of items, format, and level of difficulty. The measures of the four entry variables and the posttest score provided the predictive database for the formulation of adaptive grouping.

(b) With the cluster analysis technique, students who had similar characteristics according to the predictive database are clustered in one of a reasonably small number of mutually exclusive groups. The purpose of grouping was to aggregate students so that those within a group were relatively homogeneous among themselves and relatively different from students in other groups. Hansen et al. assumed that for instructional purposes, approximately three to five groups best characterize the cultural and psychological characteristics of the group which are to be differentially treated.

(c) The new students who would receive the adaptive treatments were classified into one of the groups by discriminant analysis. This is a method used to seek the linear combination of variables that will maximize the difference between the groups relative to the difference within the groups.

(d) Multiple regression analysis was used to derive differential predictions about the number of instructional items (examples) to assign to the student. From regression equations based on group parameter characteristics, initial performance estimates were derived for all subjects. In order to derive a decision rule for converting the performance estimate on the test into the prescription example number, a quasi-standard score (Z score) procedure was employed. To systematize matching of the Z score to example prescriptions, the latter were treated as whole numbers on a score continuum having a median number and a range from the minimum to the maximum number of examples for learning each rule. For example, minimum = 2, median = 6, and maximum = 10. A student who had a predicted score close to the mean ($Z = 0$) on a given rule received a prescription of the median number of examples. If the student was predicted to be performing below or above the mean, he or she received more or fewer examples. For example, for a student who was below one standard deviation from the mean, nine examples were given. This decision rule was arbitrary.

(e) The initial prescription derived from the group characteristics were redefined during instruction on the basis of the student's performance on the immediately preceding rule posttest (termed *minitest*). The decision rule employed in making this refinement was again arbitrary. For example, two examples were added following the rule prescription for a minitest score of 0; one example was added for a minitest score of 1; one example was subtracted for a minitest score of 3; two examples were subtracted for a minitest score of 4; no adjustment was made for a minitest score of 2. These adjustments were made only on the next rule in the sequence. To maintain the arbitrarily established boundaries of minimum and maximum, the prescriptions were not limited to vary beyond the minimum or maximum number of examples regardless of the minitest performance.

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 poorest 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 does not have strong justification 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 described above. A preliminary evaluation study showed the superior effect of the adaptation of contextual density over a standard contextual density condition or learner-control condition.

The Ross and Morrison's approaches for the contextual adaptation alone cannot be considered micro-adaptive systems because they do not have the capability of performing the 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 micro-adaptive 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 be incorporated in the regression analysis model, the incorporation has not yet been fully accomplished.

22.4.2.3. 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. The Bayes'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's 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 (using the beta, β, distribution) 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 an appropriate number of test items from this table that seem adequate to predict mastery of each objective. Rothen and Tennyson (1978) modified Novick and Lewis's (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. The implementation of this procedure requires the establishment of three parameters:

(a) An estimate is made of the student's initial ability based on prior knowledge. The beta distribution is used to characterize this information in probabilistic terms. This involves making an initial estimate of probability by administering a pretest and comparing the score to historically accumulated data (i.e., information collected from previous students). Rothen and Tennyson used the procedure described by Novic and Jackson (1974) in the selection of a particular beta distribution to characterize prior briefs. Novick and Lewis (1974) suggested using a prior distribution, $\beta(a, b)$, which assign a probability slightly greater than .5 to the region above the criterion level set in advance to determine the mastery of the given objective.

(b) A criterion level (π_o) for the objective is set. To decide on a student's attainment of mastery, it is necessary to select a minimum acceptance probability that a student's true level (π) exceeds or is equal to the criterion. For a test of length n with a student's score of x, a value of π_o must be selected such that the probability $(\pi \geq \pi_o /x, n) \geq .5$. This is equivalent to at least a 50% certainty that the student's level of functioning is above π_o.

(c) The loss ratio (R) is defined as the disutilities associated with a false advance to a false retain decision. R refers to the relative losses associated with advancing a learner whose true level of functioning is below π_o and retaining a learner whose true level exceeds π_o.

Specification of these parameters, $\beta(a, b)$, R, and π_o affects the minimum necessary instructional presentation. As the prior distribution approaches unity, the length of instructional presentation decreases. A large loss ratio increases the length of instructional presentation to allow the possibility of high posterior probability of mastery. If the criterion level approaches 1, the instructional length is increased to provide adequate information about a student's level of functioning in the interval of the criterion.

The amount of instruction is selected by establishing the operating level for the student. The operating level is updated with each on-task response and compared to the posterior distribution. If the student's operating level is greater than or equal to the posterior probability, the student is judged to have correctly mastered the objective, and no further instruction is given. If the student's operating level is below that generated from the posterior distribution, his or her posterior distribution is used as a prior distribution with the same parameters for the criterion level and loss ratio as before. A new instructional presentation is then generated. This procedure is applied iteratively until either the student is judged to have mastered the objective or the instructional materials pool is exhausted.

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 her or his on-task performance (Tennyson & S. Park, 1984; Tennyson, Park & Christensen, 1985).

If the instructional system uses mastery learning as its primary goal (Glaser, 1963) 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. Tennyson and Rothen (1977) used a task-related aptitude measure (logical reasoning ability) in deciding the loss ratio and included a response-confidence measure in weighting the on-task performance score. However, these procedures were employed without a theoretical base. 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 was not only more effective than nonresponse-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.

22.4.2.4. 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 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 (R) for performing the tasks (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 obtained rule set and repeated again 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.

Once a basic rule set $B(R_m)$ has been identified, and if B can be considered the student's entering knowledge from assessment of prior knowledge, it is possible to determine whether or not given problems might be solved by applying rules to other available rules, and, correspondingly, which rules might be learned (derived) as a result. The rule set that might be learned (at a given stage) by the student with exact knowledge of the rules in B is denoted as B^2. The rule set immediately learnable, given the rules in B^{n-1}, is denoted B^n. Each rule in B^n represents a unit of knowledge that might be acquired by the student whose entry knowledge (B) includes only the initial rules (R_m). In general, B^n will be a far more encompassing and powerful rule set than the initial rule set R_m from which B^n is derived. The ability to solve problems associated with B^n comes about gradually as a result of solving sequences of simple problems associated with $B, B^2, \ldots, B^{n-1}$.

Hence, given any random selection of problems from the domain and a set of rules available in the learner's knowledge, it is possible to determine algorithmically which of the problems might be learned at any given stage and which problems require further instruction (e.g., in the form of prior problem-solving experience). In turn, this makes it possible to arrange the problems algorithmically in a learnable order. In general, it would be impossible or impractical to teach directly all of the solution rules contained in B^n.

The algorithmic sequence can be determined by computer alone, without the student's involvement. The operational procedure of the computer program is as follows: The program takes as input the initial set of rules, which is available in the student's knowledge, and an arbitrary list of problems. It then attempts the given problem in turn. Solved problems are added to a learnable sequence, and rules derived from solving problems are added to the rule set. Failed problems are retained on a failing problem list and reattempted after all problems are solved, or until the number of failed problems reaches a prespecified limit. This process has the effect of reordering presented problems so that each problem is solvable on its first presentation. That is, the program outputs may be used to discard redundant problems, to rearrange problems, or to add intermediate problems so that unsolved problems become solvable.

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 Durnin (1977) reported that a testing method based on the algorithmic sequence could assess the student's performance potential 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 both on 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 & E. 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 which define the required actions and then by joining these attributes with the student's logical operations.

22.4.2.5. Other Micro-Adaptive Models. For the last 2 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. McComb and McDaniel identified the important learning characteristics (e.g., reading/reasoning and memory ability, anxiety, and curiosity, etc.) from the results of multiple stepwise regression analyses of existing student performance data. To compensate for the student's deficiencies of 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 included in this review because they do not have true on-task adaptive capability, which is the most important criterion to be qualified as a micro-adaptive 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.

22.4.3 Treatment Variables in Micro-Adaptive Models

As reviewed above, micro-adaptive models are primarily developed to adapt two instructional variables: amount of content to be presented and presentation sequence of 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 (Tennyson & Rothen, 1977; Park & Tennyson, 1980) 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 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, etc.) 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 showed higher test scores 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, while that of on-task measures increases as the instruction progresses.

As reviewed above, a common characteristic of micro-adaptive 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 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 recent 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 mostly limited 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 micro-adaptive instructional models, so the response sensitive procedures can be utilized for more broad and complex domain areas.

22.4.4 Intelligent Tutoring Systems

Intelligent tutoring systems (ITS) 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 (see 19.3). As in any other instructional systems, ITSs have components representing content to be taught, the 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 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 micro-adaptive model in which the decision is entirely based on quantitative data. (For a detailed description of the ITS components and the AI methods used in the systems, see Chapter 19.)

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 (see 19.4). Some ITSs have not just 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 (Seidel & Park, 1994; see also 19.5). 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 the ITS methods and techniques (Park & Seidel, 1989; Seidel, Park & Perez, 1988). However, theoretical issues of how to learn and teach with emerging technology, including AI, would continue to remain the most challenging problem.

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

As reviewed above, micro-adaptive systems, including ITS, 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 for selectively applying aptitude variables in adaptive instruction is continuing. It has been suggested to integrate some aptitude variables in the micro-adaptive system. For example, Park and Seidel (1989) recommended to include several aptitude variables in the ITS student model and use them in the diagnostic and tutoring processes.

22.5.1 A Two-level Model of Adaptive Instruction

To integrate the ATI approach in a micro-adaptive model, Tennyson and Christensen (1985, 1988; also see Tennyson & Park, 1987) have proposed a two-level model of adaptive instruction. This two-level model is partially based on the findings of their own research in adaptive instruction over the last 2 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 of 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, and embedded refreshment and remediation) are determined based on the evaluation of the on-task performance. However, the response-sensitive procedure used in this micro-adaptation level has two major limitations, as discussed in 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 of handling only limited types of learning tasks (e.g., concept and rule learning).

For variables to be considered in the macro-adaptive process, Tennyson and Christensen (1988) identified the types of learning objectives, instructional variables, and the enhancement strategies for different types of memory structure (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.

22.5.2 On-Task Performance and Response-Sensitive Strategies

Studies reviewed in the micro-adaptive models demonstrated the superior diagnostic power of on-task performance measure to pretask measures and the stronger effect of response-sensitive adaptation to 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 in spite of 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 could be stable in nature, while others could be 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, 1988) 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 learned in the immediately preceding unit becomes the most important factor in learning the next unit, and motivational level for learning the next unit may not be the same as in 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 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 effective at other stages.

22.5.3 Diagnostic Power of Aptitudes and On-Task Performance

As discussed above, the change of aptitudes during the learning process suggests that the diagnostic power of premeasured aptitude variables for assessing his or her learning needs, including instructional treatments, decreases as the learning continues. In contrast, the diagnostic power of on-task performance increases because it reflects the most updated and integrated reflection of aptitude and other variables involved in the learning. In contrast, the student's on-task performance in the initial stage of learning may not be as powerful as in the later stage of learning because of the student's lack of understanding about the nature of the task, specific learning requirements in the task, and his or her ability related to the learning of the task. Therefore, during the initial stage of instruction, specific aptitude variables like prior knowledge and general intellectual ability may be more valuable than on-task performance or response in prescribing the best instructional treatment for the student.

The decrease in predictive power of the premeasured aptitude variables and the increase in that of on-task performance can be represented as Figure 22-1.

22.5.4 Response-Sensitive Adaptation

Figure 22-1 suggests that an adaptive instructional system should be a two-stage approach: (a) adaptation to the selected aptitude variable, and (b) 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 value of the pretest performance data becomes less important, and the most recent performance data become more important.

The response-sensitive procedure is particularly important because it can determine and adjust learning prescriptions

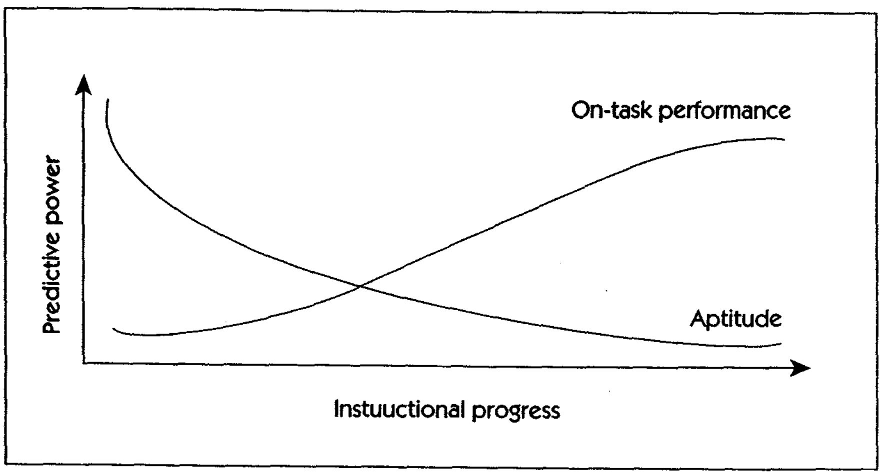

Figure 22-1. Predictive power of aptitudes and on-task performance.

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 effect 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 learning needs and generate instructional treatments entirely based 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 with an on-task analysis. Without considering the content structure, the student's response reflecting his or her knowledge state 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 to instantly generate instructional treatment (i.e., knowledge) appropriate for the misconception (see Chapter 19).

22.5.5 On-task Performance and Adaptive Learner-Control

A similar curve to the instructional diagnostic power of aptitudes (Fig. 22-1) 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 would be relatively low, and the student would not be able to choose the best strategies for learning. However, as the process of instruction and learning continues and external or self-assessment about the student's own ability is repeated, her or his familiarity with the subject and ability to learn it would increase. Thus, as the instruction progresses, the student would be able to make better decisions in selecting strategies for learning the subject. This argument is supported by research evidence that the strong effect of learner-control strategies are mostly found in relatively long-term studies (Seidel, Wagner, Rosenblatt, Hillelsohn & Stelzer, 1978; Snow, 1980), while scattered effects are found usually in short-term experiments (Carrier, 1984; Ross & Rakow, 1981).

The speed, degree, and quality of obtaining the self-regulatory ability in the learning process, however, would be different between students (Gallangher, 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 the learner the options for controlling the instructional process based on the progress of the learner's 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 for giving the learner-control option but also what kind of control options (e.g., selection of contents, learning activities, etc.) 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.

22.6 INTERACTIVE COMMUNICATION IN ADAPTIVE INSTRUCTION

The response-sensitive strategies in CBI have been mostly applied to simple student-computer interactions such as multiple-choice, true-false, and short-answer types of question-asking 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 computer (see 19.2.3). 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 is relatively slow, it is certain that future adaptive instructional systems, including ITS, 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. As Wenger (1987) defined, 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.

22.6.1 Process of Instructional Communication

To develop a communication model for instruction, the process of instructional communication should first be understood. Seidel and his associates (Seidel, Compton, Kopstein, Rosenblatt & See, 1969) divided instructional communication into teaching and assessment channels existing between the instructor and student. (Fig. 22-2 is adopted from Seidel et al. with modifications.) Through the teaching channel, the instructor presents the student communication materials via the interface medium (e.g., computer display). The communication materials are generated from the selective integration of the instructor'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 instructor's expectation. The student's understanding and learning of the materials is 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 instructor. Seidel et al. (1969; Seidel, 1971) called the communication process from the student to the instructor the *assessment channel.* Through this process, the instructor 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 to the state that the instructor 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. Since specific combinations of questions and responses between the student and instructor 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.

22.6.2 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 & Rouseau, 1981). However, few principles or procedures for asking diagnostic questions in CBI or ITS have been developed. Most diagnostic processes in CBI and ITS 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 ITS (see also 19.3.2): (a) overlay method for comparing the student's current knowledge structure with the expert's, and (b) 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 tutoring undergraduates in research methods, Graesser (1993) identified a five-step dialogue pattern to implement in an ITS. They are: (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 the student's understanding of the answer. According to Graesser's observation, tutor questions were primarily motivated by curriculum scripts and the process of coaching student's 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 counter examples; (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 (see 7.4.3) and Socratic dialogue techniques in their reciprocal teaching (see also 23.4.1.3.4). While the expert scaffolding provides guidance for the tutor's involvement or provision of aids in the learning process, the Socratic dialogue techniques suggest what kinds of questions should be asked to diagnose the student's learning needs. Five ploys are important to present in the diagnostic questions: (a) Systematic varied cases are asked to help the student focus on relevant facts; (b) counter examples and hypothetical cases are asked 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: (a) explicating the goal and objectives of the lessons, and (b) 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 postrequisite) between the instructional goal and content elements and the constraints for the use of the learned content.

As the above review suggests, efforts for generating the principles of tutoring strategies (diagnosis and explana-

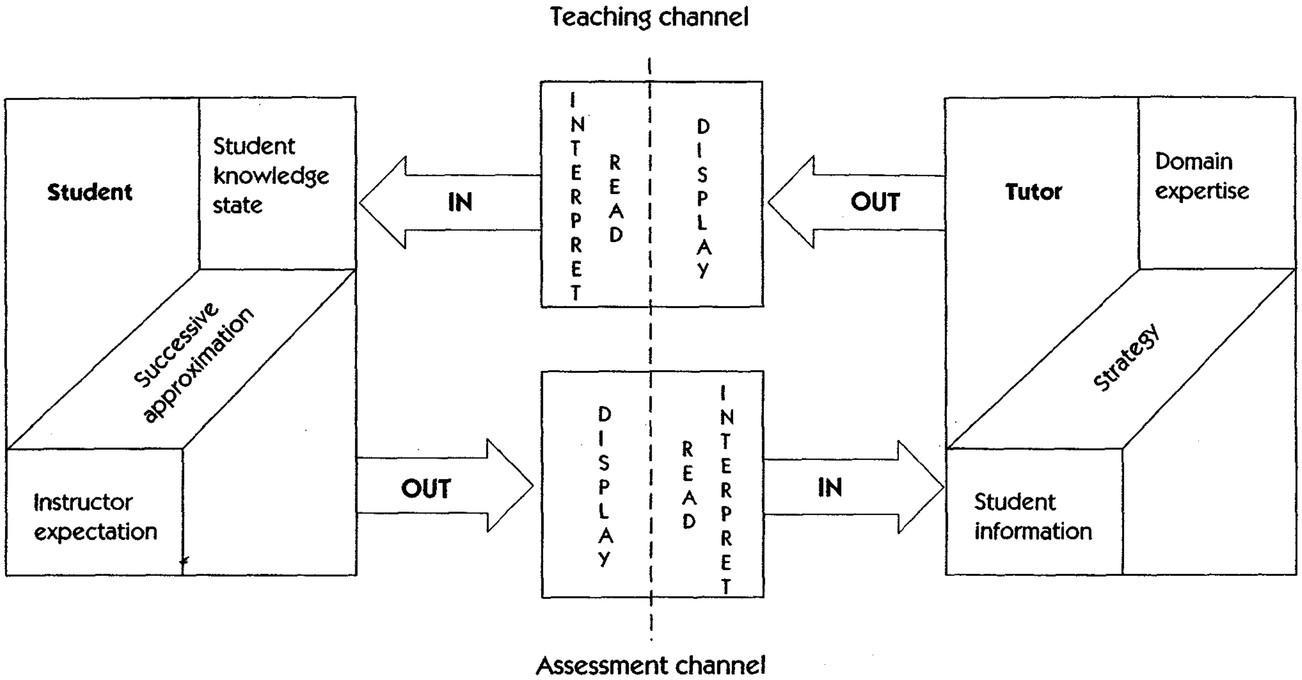

Figure 22-2. Process of instructional communication. (Adapted from Siedel et al., 1969.)

tions) have continued from the observation of human tutoring activities (e.g., Berliner, 1991; Borko & Livingston, 1989; Leinhardt, 1989; Putnam, 1987), and from simulation and testing of tutoring processes in ITS environments (Ohlson & Rees, 1991; see Chapter 19.) However, specific principles and practical guidelines for generating questions and explanations in an on-task adaptive system have yet to be developed.

22.6.3 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 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 be nonrule governed. Also, she says that tutoring dialogues should be contexualized, and the contexualization 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.

22.7 A MODEL OF ADAPTIVE INSTRUCTIONAL SYSTEMS

In the above section, I 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 continuously every component in the instructional system based on the student's on-task performance and the interactions between the student and system. However, almost all adaptive instructional systems, including ITSs, have been developed with emphasis on a few specific aspects or functions of instruction. Therefore, we present a conceptual model for developing a complete adaptive instructional system (Fig. 22-3). 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, Perez & Seidel, 1987).

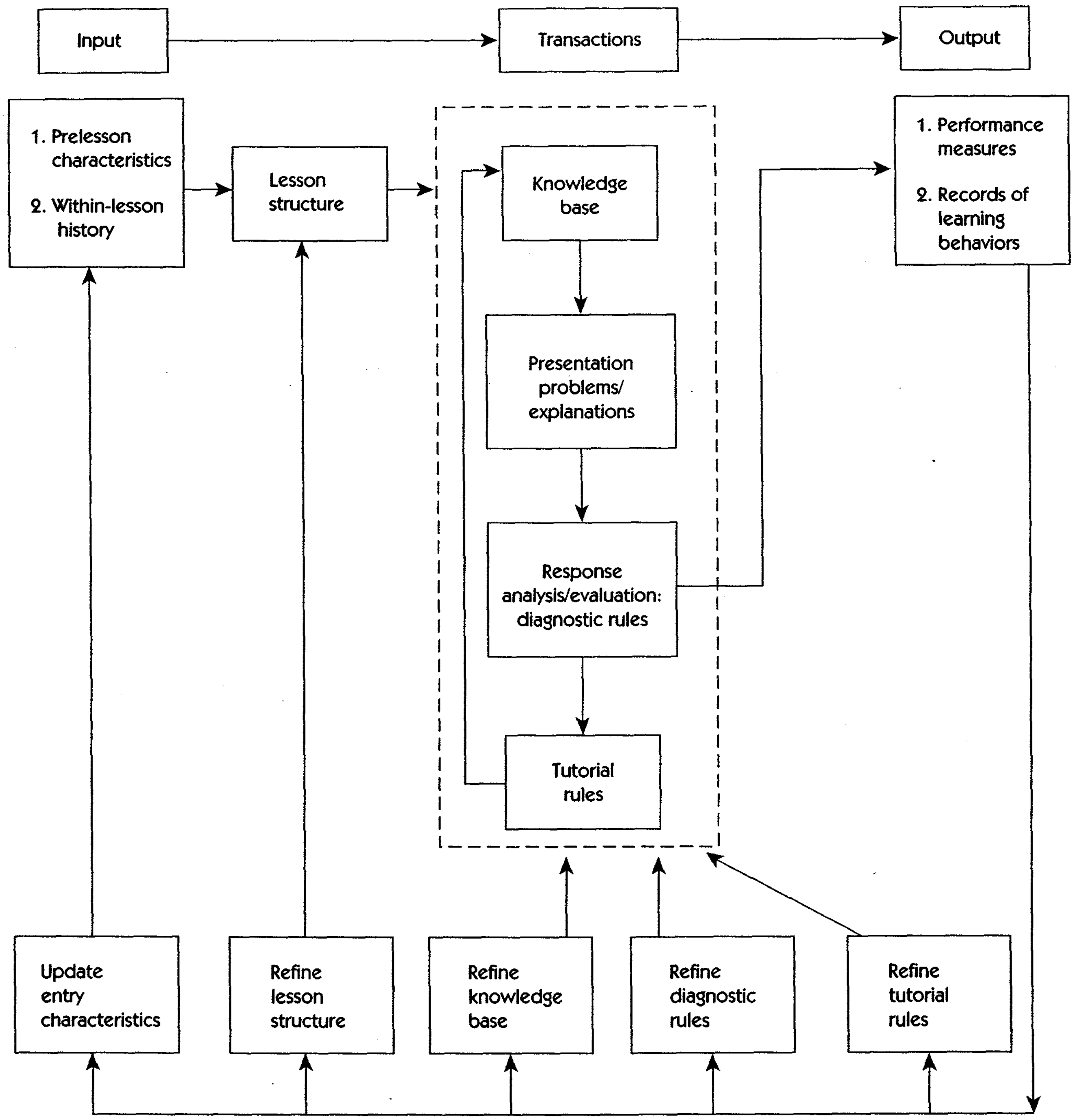

Figure 22-3. A model of adaptive instruction (Park et al., 1987). (Originally adapted from Seidel, 1971.)

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 a 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 Figure 22-3 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 the evaluation information of the performance (i.e., output measures).

The transaction stage consists of the interactions between the student and 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 Gallangher, 1994; Weinstein & Mayer, 1986), expert heuristics (Jonassen, 1988), and response-sensitive strategies discussed in the earlier section of this chapter.

The output stage mainly consists 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, the human monitor may be required to perform that task.

22.8 CONCLUSION

Adaptive instruction has a long history (Reiser, 1987). However, systematic effort aimed at developing adaptive instructional systems was not made until the early 1900s. The effort for developing adaptive instructional systems has taken different approaches: macro-adaptive, ATI, and micro-adaptive. Macro-adaptive 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. Micro-adaptive 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 an alternative educational system because of their demonstrated effectiveness. However, most of the macrosystems were discontinued without much success because of the difficulty associated with the development and implementation of the systems, 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 theoretical appealing and practical application possibilities. However, the results are not consistent and have provided little implications for developing an adaptive instructional system.

Using computer technology, a number of different micro-adaptive instructional systems have been developed. However, their applications have 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.

Another contribution to the limited success of adaptive instructional systems can be attributed to the unverified theoretical assumptions that were used for the development of the systems. Particularly, ATI, including the achievement and treatment interactions, has been used as the theoretical bases for many ATI studies. However, the variability of ATI research findings suggests that the theoretical assumptions used in ATI research 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 becomes less important as the instruction progresses. In the meantime, the student's on-task performance (i.e., response to the given problem or task) becomes more important for diagnosing the student's learning needs (see Fig. 22-1) because on-task performance is the integrated reflection of many verifiable and unverifiable variables involved in the learning.

Therefore, I 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) demonstrated the effects of response-sensitive strategies. However, the application of the response-sensitive strategy has been limited to simple tasks such as vocabulary acquisition and concept learning because of the technical limitations of handling the complex interactions involved in learning more sophisticated tasks such as problem solving. However, ITSs developed in the last 2 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 significantly contributed 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, I 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 & Palinscar, 1989; Leinhardt, 1983). Further research for 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 different types of information available in the system, I 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 need 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 presented in Figure 22-3 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 for developing more powerful adaptive instructional systems.

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