5. COGNITIVE PERSPECTIVES IN PSYCHOLOGY

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5.1 INTRODUCTION

The purpose of this chapter is to discuss some of the developments in cognitive psychology that have been influential in educational technology research. Since cognitive psychology is a broad, eclectic, and sometimes elusive discipline, this chapter is of necessity selective. Nonetheless, it provides discussion of the most important research in cognitive psychology that has a bearing on the theory and practice of educational technology.

Educational technology came of age as a discipline at a time when relevant psychological theory was based almost entirely on behavioral principles (see 2.2). This meant that the procedures and practice of educational technology evolved to accommodate behavioral accounts of learning and instruction (Winn, 1989). History teaches us that theories change more readily than practice. Therefore, when researchers started to develop cognitive theories that compensated for the inadequacy of behaviorism to explain many aspects of human activity, the technologies and practices by means of which psychological theory is applied changed much more slowly, and in some cases not at all. The practices recommended by some schools of thought in instructional design are still exclusively behavioral. This chapter is colored by the tension that exists between some aspects of traditional practice in educational technology and cognitive theory, a tension that arises from the difficulty of trying to reconcile one kind of theory with procedures for application developed for another kind.

The different rates of change in the theory and practice of educational technology mean that the true importance of research in cognitive psychology to our field must be examined in its historical context. For this reason, the chapter begins with a brief review of the antecedents of cognitive theory and of behaviorism against which it reacted. The historical development of cognitive psychology and cognitive science is addressed in a little more detail. The next two sections deal with two of the cornerstones of cognitive theory, mental representation, and mental processes. It will become clear that these topics are not entirely dissociable one from the other. Nonetheless, we feel that this somewhat artificial distinction is a better compromise for the sake of clarity than the muddle that would surely ensue from trying to treat both at once. The final section speaks specifically to the relevance of cognitive psychology to the practice of educational technology, namely, instructional design. It examines ways in which cognitive theory has been brought to both the theory of instruction and the design procedures by means of which that theory is applied to practical tasks.

5.2 HISTORICAL OVERVIEW

Most readers will already know that cognitive theory came into its own as an extension of (some would say a replacement of) behavioral theory (see 2.2.1). However, many of the tenets of cognitive theory are not new and date back to the very beginnings of the autonomous discipline of psychology in the 19th century. We therefore begin with a brief discussion of introspection and of Gestalt theory before turning to the story of cognitive psychology's reaction to behaviorism.

5.2.1 Introspection

One of the major forces that helped psychology emerge as a distinct discipline at the end of the 19th century was the work of the German psychologist Wundt (Boring, *1950).* Wundt made two significant contributions, one conceptual and the other methodological. First, he clarified the boundaries of the new discipline. Psychology was the study of the inner world, not the outer world, which was the domain of physics. And the study of the inner world was to be the study of thought, or mind, not of the physical body, which was the domain of physiology. At first glance, these two distinctions may strike us as somewhat naive. However, it is worth noting that a great deal of recent research in cognitive psychology has looked at the issue of how the physical world is mapped onto memory, and in some cases it is not always clear where the physical world ends and the mental world begins. Also, there is now a growing interest in neurophysiological explanations of perception and cognition. This interest is occurring at a time when philosophers and psychologists are questioning Cartesian dualism, which proposes that mind and body are separate and which has held sway in Western thought since the 17th century. The distinction between mind and brain is becoming blurred. Thus, today, physics and physiology are not necessarily cleanly separated from psychology.

Wundt's methodological contribution was the development of introspection as a means for studying the mind. Physics, and to a large extent physiology, deals with phenomena that are objectively present and therefore directly observable and measurable. Thought is both highly subjective and intangible. Therefore, Wundt proposed, the only access to it, if one was to study it directly, was for a person to examine his or her own thoughts. And the only way to do that was through introspection. Wundt developed a program of research that extended over many decades and attracted adherents from laboratories in many countries. Typically, his experimental tasks were simple: pressing buttons, watching displays. The data of greatest interest were the descriptions his subjects gave of what they were thinking about as they performed the tasks.

On the face of it, Wundt's approach was very sensible. You best learn about things by studying them directly. And the only direct route to thought is via a subject's description of his or her own thinking. The danger of introspection lies in the difficulty persons have thinking about their own thinking. Behaviorists would soon decry the lack of objectivity in the method. What is more, we have to ask whether the act of thinking about thinking interferes with and changes the thinking that one is interested in studying. Is there an "uncertainty principle" at work whereby the act of thinking about thought changes its very nature?

It is important to note that, in spite of criticism that led to its ultimate demise, introspection (the first psychology) was unashamedly cognitive. What is more, the same general access route to cognitive processes is used today in think-aloud protocols (Ericsson & Simon, 1984) obtained while subjects perform natural or experimental tasks. The method is respected, judged to be valid if properly applied, and essential to the study of thought and behavior in the real world or in simulations of it.

5.2.2 Gestalt Psychology

The word *Gestalt* is a German noun that

> has two meanings: besides the connotation of "shape" or "form" as a property of things, it has the meaning of a concrete individual and characteristic entity, existing as something detached and having a shape or form as one of its attributes. Following this tradition, in Gestalt theory, the word *Gestalt* means any segregated whole (Hartman, *1935).*

Thus, Gestalt psychology is the study of how people see and understand the relation of the whole to the parts that make up that whole.

Wertheimer (1924) stated that Gestalt psychology was not trying to find the meaning of each individual part at the expense of the whole. He stated:

> Gestalt theory will not be satisfied with sham solutions suggested by a simple dichotomy of science and life. Instead, Gestalt theory is resolved to penetrate the problem itself by examining the fundamental assumptions of science. It has long seemed obvious—and is, in fact, the characteristic tone of European science—that "science" means breaking up complexes into their component elements. Isolate the elements, discover their laws, then reassemble them, and the problem is solved. All wholes are reduced to pieces and piecewise relations between pieces. The fundamental "formula" of Gestalt theory might be expressed this way: There are wholes, the behavior of which is not determined by that of their individual elements, but where the part-processes are themselves determined by the intrinsic nature of the whole. It is the hope of Gestalt theory to determine the nature of such wholes (Wertheimer, 1924).

Although the major features of this "new" psychology were developed by Wertheimer, his two protégés, Kohler and Koffka, were responsible for the wide dissemination of this school of thought. This spread was assisted by the rise in Germany of the Nazi party in 1933. Hitler expelled Wertheimer, Levin, von Hornbostel, Stern, Werner, and other Gestalt scholars, ensuring the spread of the concept. Koffka was appointed a research professor at Smith College, and Kohler would soon be at Harvard. Both had been giving lecture tours explaining the principles and concepts of this new school.

One of the best illustrations of the whole being different from the sum of the parts is provided by Ehrenfels in a musical example. If a melody is played on an instrument, it is recognizable. If the melody is played again, but this time in another key, it is still recognizable. However, if the same notes, in the same key, were played in a different sequence, the listener will not recognize any similarity between the first and the second melody. As an example, if the sequence of notes for the first melody was *e e f g g f e d c c d e e d d,* and the second melody played was *b b c d d c b a g g a b b* a a, the listener would recognize the melody immediately as being the same even though different notes are involved. But if the second sequence used the same notes but in a different order, *e e g g f f c c d d e e e d d,* the similarity would not be recognized unless, of course, the listener understood the precise way in which the melody has been transformed.

Based on this difficulty, and the ability of a person to recognize and even reproduce a melody in a key different from the original one.

> Ehrenfels concludes that the resemblance between spatial and tonal patterns rests upon something other than a similarity of their accompanying elements. The totals themselves, then, must be different entities than the sums of their parts.

> In other words, the *"Gestaltqualität"* ("form quality") or whole has been reproduced: the elements or Parts have not" (Hartmann, 1935).

The central tenet of Gestalt theory—that our perception and understanding of objects and events in the world depends on the appearance and actions of whole objects, not of their individual parts — has had some influence on the evolution of research in educational technology. The key to that influence are the well-known Gestalt laws of perceptual organization, codified by Wertheimer (1938). These include the principles of "good figure, " "figure-ground separation, " and "continuity." These laws formed the basis for a considerable number of message design principles (see 26.2) (Fleming & Levie, 1978), in which Gestalt theory about how we perceive and organize information that we see is used in prescriptive recommendations about how to present information on the page, or screen. A similar approach to what we hear is taken by Hereford and Winn (1994).

More broadly, the influence of Gestalt theory is evident in much of what has been written about visual literacy (see 16.4). In this regard, Arnheim's book *Visual Thinking* (1969) is a key work. It was widely read and cited by scholars of visual literacy and proved influential in the development of that movement.

Finally, it is important to note the recent renewal of interest in Gestalt theory (Henle, 1987; Epstein, 1988). The Gestalt psychologists provided little empirical evidence for their laws of perceptual organization beyond everyday experience of their effects. Recently, perceptual psychologists (Pomerantz, 1986; Rock, 1986) have provided explanations for how perceptual organization works from the findings of controlled experiments. The effects of such stimulus features as symmetry on perceptual organization has been explained in terms of the "emergent properties" (Rock, 1986) of what we see in the world around us. We see a triangle as a triangle, not as three lines and three angles. Emergent properties, of course, are the same as the Gestaltist's "whole" that has features all its own that are, indeed, greater than the sum of the parts.

5.2.3 The Rise of Cognitive Psychology

Behavioral theory is described in detail elsewhere in this handbook (see 2.2). Suffice it to say that behaviorism embodies two of the key principles of positivism: that our knowledge of the world can only evolve from the observation of objective facts and phenomena; and that theory can only be built by applying this observation in experiments where only one or two factors are allowed to vary as a function of an experimenter's manipulation or control of other related factors. The first of these principles therefore banned from behavioral psychology unobservable mental states, images, insights, and Gestalts. The second principle banned research methods that involved the subjective techniques of introspection, phenomenology, and the drawing of inferences from observation rather than from objective measurement. Ryle's (1949) relegation of the concept of "mind" to the status of 'the ghost in the machine, " both unbidden and unnecessary for a scientific account of human activity, captures the behaviorist ethos exceptionally well.

Behaviorism's reaction against the suspect subjectivity of introspection was necessary at the time if psychology were to become a scientific discipline. However, the imposition of the rigid standards of objectivism (see 7.3) and positivism excluded from accounts of human behavior many of those experiences with which we are extremely familiar. We all experience mental images, feelings, insight, and a whole host of other unobservable and unmeasurable phenomena. To deny their importance is to deny much of what it means to be human (Searle, 1992). Cognitive psychology has been somewhat cautious in acknowledging the ability or even the need to study such phenomena, often dismissing them as "folk psychology" (Bruner, 1990). Only recently, this time as a reaction against the inadequacies of cognitive rather than behavioral theory, do we find serious consideration of subjective experiences. (These are discussed in Bruner, 1991; Clancey, 1993; Edelman, 1992; Searle, 1992; and Varela, Thompson & Rosch, 1991, among others. They are also touched on elsewhere in this handbook.)

Cognitive psychology's reaction against the inability of behaviorism to account for much human activity arose mainly from a concern that the link between a stimulus and a response was not straightforward, that there were mechanisms that intervened to reduce the predictability of a response to a given stimulus, and that stimulus-response accounts of complex behavior unique to humans, like the acquisition and use of language, were extremely complex and contrived. (Chomsky's [1964] review of Skinner's [1957] S-R account of language acquisition is a classic example of this point of view and is still well worth reading.) Cognitive psychology therefore focuses on mental processes that operate on stimuli presented to the perceptual and cognitive systems, and which usually contribute significantly to whether or not a response is made, when it is made, and what it is. Whereas behaviorists claim that such processes cannot be studied because they are not directly observable and measurable, cognitive psychologists claim that they *must* be studied because they alone can explain how people think and act the way they do.

Let me give two examples of the transition from behavioral to cognitive theory. The first concerns memory, the second mental imagery.

Behavioral accounts of how we remember lists of items are usually associationist. Memory in such cases is accomplished by learning S-R associations among pairs of items in a set and is improved through practice (Gagné, 1965; Underwood, 1964). However, we now know that this is not the whole story and that mechanisms intervene between the stimulus and the response that affect how well we remember. The first of these is the collapsing of items to be remembered into a single "chunk." Chunking is imposed by the limits of short-term memory to roughly seven items (Miller, 1956). Without chunking, we would never be able to remember more than seven things at once. When we have to remember more than this limited number of items. we tend to learn them in groups that are manageable in short-term memory, and then to store each group as a single unit. At recall, we "unpack" (Anderson, 1983) each chunk and retrieve what is inside. Chunking is more effective if the items in each chunk have something in common, or form a spatial (McNamara 1986; McNamara, Hardy & Hirtle, 1989) or temporal (Winn, 1986) group.

A second mechanism that intervenes between a stimulus and response to promote memory for items is interactive mental imagery. When people are asked to remember pairs of items and recall is cued with one item of the pair, performance is improved if they form a mental image in which the two items appear to interact (Paivio, 1971, 1983; Bower, 1970). For example, it is easier for you to remember the pair *Whale Cigar* if you imagine a whale smoking a cigar. The use of interactive imagery to facilitate memory has been developed into a sophisticated instructional technique by Levin and his colleagues (Morrison & Levin, 1987; Peters & Levin, 1986). The considerable literature on the role of imagery in paired-associate and other kinds of learning is summarized by Paivio (1971, 1983; Clark & Paivio, 1991).

The importance of these memory mechanisms to the development of cognitive psychology is that, once understood, they make it very clear that a person's ability to remember items is improved if the items are meaningfully related to each other or to the person's existing knowledge. The key word here is *meaningful.* For now, we shall simply assert that what is meaningful to people is determined by what they can remember of what they have already learned. This implies a circular relationship among learning, meaning, and memory—that what we learn is affected by how meaningful it is, that meaning is determined by what we remember, and that memory is affected by what we learn. However, this circle is not a vicious one. The reciprocal relationship between learning and memory, between environment and knowledge, is the driving force behind established theories of cognitive development (Piaget, 1968) and of cognition generally (Neisser, 1976), as we shall see in our examination of schema theory. It is also worth noting that Ausubel's (1963) important book on meaningful verbal learning proposed that learning is most effective when memory structures appropriate to what is about to be learned are created or activated through advance organizers. More generally, then, cognitive psychology is concerned with meaning, or semantics, while behavioral psychology is not.

Mental imagery provides another interesting example of the differences between behavioral and cognitive psychology. Imagery was so far beyond the behaviorist pale that Mandler's article, which reintroduced the topic, was subtitled "The return of the ostracized." Images were, of course, central to Gestalt theory, as we have seen. But because they could not be observed, and because the only route to them was through introspection and self-report, they had no place in behavioral theory.

Yet we can all, to some degree, conjure up mental images. We can also deliberately manipulate them. Kosslyn, Ball, and Reiser (1978) trained their subjects to "zoom" in and out of images of familiar objects and found that the "distance" between the subject and the imagined object constrained the subject's ability to describe the object. To discover the number of claws on an imaged cat, for example, the subject had to move closer to it in the mind's eye.

This ability to manipulate images is useful in some kinds of learning. The method of "Loci" (Kosslyn, 1985; Yates, 1966), for example, requires a person to create a mental image of a familiar place in the mind's eye and to place in that location images of objects that are to be remembered. Recall consists of mentally walking through the place and describing the objects you find. The effectiveness of this technique, which was known to the orators of ancient Greece, has been demonstrated empirically (Cornoldi & De Beni, 1991; De Beni & Cornoldi, 1985).

Mental imagery will be discussed in more detail in the section on representation (5.3). For now, we will draw attention to two methodological issues that are raised by its study. First, some studies of imagery are symptomatic of a conservative color to some cognitive research. As Anderson (1978) has commented, any conclusions about the existence and nature of images can only be inferred from observable behavior. You can only really tell if the Loci method has worked if a person can name items in the set to be remembered. On this view, the behaviorists were right. Objectively observable behavior is all even cognitive researchers have to go on. This means that cognitive psychology has to study mental representation and processes indirectly and to draw conclusions about them by inference rather than from direct measurement. (This will doubtless change as techniques for directly observing brain functions during cognitive activity become available and reliable. See Farah, 1989.)

The second methodological issue is exemplified by Kosslyn's (1985) use of introspection and self-report by subjects to obtain his data on mental images. The scientific tradition that established the methodology of behavioral psychology considered subjective data to be biased, tainted, and therefore unreliable. This precept has carried over into the mainstream of cognitive research. Yet, in his invited address to the 1976 AERA conference, the sociologist Uri Bronfenbrenner (1976) expressed surprise, indeed dismay, that educational researchers do not ask subjects their opinions about the experimental tasks they carry out, nor about whether they performed the tasks as instructed or in some other way. Certainly, this stricture has eased in much of the educational research that has been conducted since 1976, and nonexperimental methodology, ranging from ethnography to participant observation to a variety of phenomenologically based approaches to inquiry is the norm for certain types of educational research (see, for example, the many articles that appeared in the mid-80s, among them Baker, 1984; Eisner, 1984; Howe, 1983; Phillips, 1983). Nonetheless, strict cognitive psychology still tends to adhere to experimental methodology, based on positivism, which makes research such as Kosslyn's on imagery somewhat suspect.

5.2.4 Cognitive Science

Inevitably, cognitive psychology has come face to face with the computer. This is not merely a result of the times in which the discipline has developed but also emerges from the intractability of many of the problems cognitive psychologists seek to solve. The necessity for cognitive researchers to build theory by inference rather than from direct measurement has always been problematic. And it seems that it will remain so until such time as the direct measurement of brain activity is possible on a large scale.

One way around this problem is to build theoretical models of cognitive activity, to write computer simulations that predict what behaviors are likely to occur if the model is an accurate instantiation of cognitive activity, and to compare the behavior predicted by the model—the output from the program—to the behavior observed in subjects. A good example of this approach is found in the work of David Marr (1982) on vision.

Marr began with the assumption that the mechanisms of human vision are too complex to understand at the neurological level. Instead, he set out to describe the functions that these mechanisms need to perform as what is seen by the eye as it moves from the retina to the visual cortex and is interpreted by the viewer. The functions Marr developed were mathematical models of such processes as edge detection, the perception of shapes at different scales and stereopsis (Marr & Nishihara, 1978). The observed electrical activity of certain types of cell in the visual system matched the activity predicted by the model almost exactly (Man & Ullman, 1981).

Marr's work has had implications that go far beyond his important work on vision, and as such serves as a paradigmatic case of cognitive science. *Cognitive science* is not called that because of its close association with the computer but because it adopts the functional or computational approach to psychology that is so much in evidence in Marr's work. By "functional" (see Pylyshyn, 1984), we mean that it is concerned with the functions the cognitive system must perform, not with the devices through which cognitive processes are implemented. A commonly used analogy is that cognitive science is concerned with cognitive software, not hardware. By "computational" (Arbib & Hanson, 1987; Richards, 1988), we mean that the models of cognitive science take information that a learner encounters, perform logical or mathematical operations on it, and describe the outcomes of those operations. The computer is the tool that allows the functions to be tested, the computations to be performed.

The tendency in cognitive science to create theory around computational rather than biological mechanisms points to another characteristic of the discipline. Cognitive scientists conceive of cognitive theory at different levels of description. The level that comes closest to the brain mechanisms that create cognitive activity is obviously biological. However, as Marr presumed, this level is virtually inaccessible to cognitive researchers, consequently requiring the construction of more abstract functional models. The number, nature, and names of the levels of cognitive theory vary from theory to theory and from researcher to researcher. Anderson (1990, Chapter 1) provides a useful discussion of levels, including those of Chomsky (1965), Pylyshyn (1984), Rumelhart and McClelland (1986), and Newell (1982), in addition to Marr's and his own. In spite of their differences, each of these approaches to levels of cognitive theory implies that if we cannot explain cognition in terms of the mechanisms through which it is actually realized, we can explain it in terms of more abstract mechanisms that we can profitably explore. In other words, the different levels of cognitive theory are really different metaphors for the actual processes that take place in the brain.

The computer has assumed two additional roles in cognitive science beyond that of a tool for testing models. First, some have concluded that, because computer programs written to test cognitive theory accurately predict observable behavior that results from cognitive activity, cognitive activity must itself be computerlike (see 19.2.3.1). Cognitive scientists have proposed numerous theories of cognition that embody the information-processing principles and even the mechanisms of computer science (Boden, 1988; Johnson-Laird, 1988). Thus we find reference in the cognitive science literature to input and output, data structures, information processing, production systems, and so on. More significantly, we find descriptions of cognition in terms of the logical processing of symbols (Larkin & Simon, 1987; Salomon, 1979; Winn, 1982).

Second, cognitive science has provided both the theory and the impetus to create computer programs that "think" just as we do. Research in artificial intelligence blossomed during the 80s, and was particularly successful when it produced intelligent tutoring systems (see 19.3; Anderson & Reiser, 1985; Anderson, Boyle & Yost, 1985; Wenger, 1987) and expert systems (see 24.8; Forsyth, 1984). The former are characterized by the ability to understand and react to the progress a student makes working through a computer-based tutorial program. The latter are smart "consultants, " usually to professionals whose jobs require them to make complicated decisions from large amounts of data.

Its successes notwithstanding, AI has shown up the weaknesses of many of the assumptions that underlie cognitive science, especially the assumption that cognition consists in the logical mental manipulation of symbols. Recently, scholars (Clancey, 1993; Dreyfus, 1979; Dreyfus & Dreyfus, 1986; Edelman, 1992; Searle, 1992) have been vigorous in their criticism of this and other assumptions of cognitive science, as well as of computational theory and, more basically, functionalism. The critics imply that cognitive scientists have lost sight of the metaphorical origins of the levels of cognitive theory and have assumed that the brain really does compute the answer to problems by symbol manipulation. Searle's comment sets the tone: "If you are tempted to functionalism, we believe you do not need refutation, you need help" (1992, p. 9). As we shall see in the last section of this chapter, cognitive science is at the point behavioral theory was in the early 60s — facing criticism from proponents of a new paradigm for psychology.

5.2.5 Section Summary

Although many of the ideas in this section will be developed in what follows, we think it is useful at this point to provide a short summary of the ideas presented so far. We have seen that cognitive psychology returned to center stage largely because stimulus-response theory did not adequately or efficiently account for many aspects of human behavior that we all observe from day to day. The research on memory and mental imagery that we briefly described indicated that psychological processes and prior knowledge intervene between the stimulus and the response, making the latter less predictable by behavioral theory. We have also seen that nonexperimental and nonobjective methodology is now deemed appropriate for certain types of research. However, it is possible to detect a degree of conservatism in mainstream cognitive psychology that still insists on the objectivity and quantifiability of data.

Cognitive science, emerging from the confluence of cognitive psychology and computer science, has developed its own set of assumptions, not least among which are computer models of cognition. These have served well, at different levels of abstraction, to guide cognitive research, leading to such applications as intelligent tutors and expert systems. However, the computational theory and functionalism that underlie these assumptions have been the source of considerable recent criticism and point perhaps to the closing of the current chapter in the history of psychology.

The implications of all of this for research and practice in educational technology will be dealt with in section 5.5. We would nonetheless like to anticipate three aspects of that discussion. First, educational technology research, and particularly mainstream instructional design practice, needs to catch up with cognitive theory. As we have suggested elsewhere (Winn, 1989), it is not sufficient simply to substitute cognitive objectives for behavioral objectives and to tweak our assessment techniques to gain access to knowledge schemata rather than just to observable behaviors. More fundamental changes are required.

Second, shifts in the technology itself away from rather prosaic and ponderous computer-assisted programmed instruction to highly interactive multimedia environments permit educational technologists to develop serious alternatives to didactic instruction. We can now use technology to do more than direct teaching. We can use it to help students construct meaning for themselves through experience in ways proposed by constructivist theory and practice described elsewhere in this handbook (see 7.4, 20.3, 20.4, 23.4, 24.6) and by Duffy and Jonassen (1992), Duffy, Jonassen, and Lowyck (1993), and others.

Third, the proposed alternatives to computer models of cognition—which explain first-person experience, nonsymbolic thinking and learning, and reflection-free cognition—lay the conceptual foundation for educational developments of virtual realities (see Chapter 15; Winn, 1993). The full realization of these new concepts and technologies lies in the future. However, we need to get ahead of the game and prepare for when these eventualities become a reality.

5.3 MENTAL REPRESENTATION

The previous section showed the historical origins of the two major aspects of cognitive psychology that are addressed in this and the next section. These are mental representation and mental processes. Our example of representation was the mental image, and passing reference was made to memory structures and hierarchical chunks of information. We also talked generally about the input, processing, and output functions of the cognitive system, and paid particular attention to Marr's account of the processes of vision.

This section deals with cognitive theories of mental representation. How we store information in memory, represent it in our mind's eye, or manipulate it through the processes of reasoning has always seemed relevant to researchers in educational technology. Our field has sometimes supposed that the way in which we represent information mentally is a direct mapping of what we see and hear about us in the world (see Knowlton, 1966; Cassidy & Knowlton, 1983; Sless, 1981). Educational technologists have paid a considerable amount of attention to how visual presentations of different levels of abstraction affect our ability to reason literally and analogically (Winn, 1982). Since the earliest days of our discipline (Dale, 1946), we have been intrigued by the idea that the degree of realism with which we present information to students determines how well they learn. More recently (Salomon, 1979), we have come to believe that our thinking uses various symbol systems as tools, enabling us both to learn and to develop skills in different symbolic modalities. How mental representation is affected by what a student encounters in the environment has become inextricably bound up with the part of our field we call *message design* (Fleming & Levie, 1993; Rieber, 1994; Chapter 7).

5.3.1 Schema Theory

The concept of "schema" is central to cognitive theories of representation. There are many descriptions of what schemata are. All descriptions concur that a schema has the following characteristics: (1) It is an organized structure that exists in memory and, in aggregate with all other schemata, contains the sum of our knowledge of the world (Paivio, 1974). (2) It exists at a higher level of generality, or abstraction, than our immediate experience with the world. (3) It consists of concepts that are linked together in propositions. (4) It is dynamic, amenable to change by general experience or through instruction. (5) It provides a context for interpreting new knowledge as well as a structure to hold it. Each of these features requires comment.

5.3.1.1. Schema as Memory Structure. The idea that memory is organized in structures goes back to the work of Bartlett (1932). In experiments designed to explore the nature of memory that required subjects to remember stories, Bartlett was struck by two things: First, recall, especially over time, was surprisingly inaccurate; second, the inaccuracies were systematic in that they betrayed the influence of certain common characteristics of stories and turns of event that might be predicted from common occurrences in the world. Unusual plots and story structures tended to be remembered as closer to "normal" than in fact they were. Bartlett concluded from this that human memory consisted of cognitive structures that were built over time as the result of our interaction with the world and that these structures colored our encoding and recall of subsequently encountered ideas. Since Bartlett's work, both the nature and function of schemata have been amplified and clarified experimentally. The next few paragraphs describe how.

5.3.1.2. Schema as Abstraction. A schema is a more abstract representation than a direct perceptual experience. When we look at a cat, we observe its color, the length of its fur, its size, its breed if that is discernible, and any unique features it might have, such as a torn ear or unusual eye colon. However, the schema that we have constructed from experience to represent "cat" in our memory, and by means of which we are able to identify any cat, does not contain these details. Instead, our "cat" schema will tell us that it has eyes, four legs, raised ears, a particular shape, and habits. However, it leaves those features that vary among cats, like eye color and length of fur, unspecified. In the language of schema theory, these are "place-holders, " "slots, " or "variables" to be "instantiated" through recall or recognition (Norman & Rumelhart, 1975).

It is this abstraction, or generality, that makes schemata useful. If memory required that we encode every feature of every experience that we had, without stripping away variable details, recall would require us to match every experience against templates in order to identify objects and events, a suggestion that has long since been discredited for its unrealistic demands on memory capacity and cognitive processing resources (Pinker, 1985). On rare occasions, the generality of schemata may prevent us from identifying something. For example, we may misidentify a penguin because, superficially, it has few features of a bird. As we shall see below, learning requires the modification of schemata so that they can accurately accommodate unusual instances, like penguins, while still maintaining a level of specificity that makes them useful.

5.3.1.3. Schema as Network. Schemata have been conceived of and described in many ways. One of the most prevalent conceptions of schema has been as a network of concepts connected by links. Illustrative is Palmer's (1975) description of a schema to represent the concept "face." The schema consists of nodes and links that describe the relations between node pairs. The central node in the network is the head, which is roughly oval in shape. The other nodes, representing other features of a face such as eyes nose, and mouth, are described in terms of their relationship to the head. The right eye is connected to the head by three links specifying shape, size, and location. Thus, the eye is an oval, like the head, but turned through an angle of 90 relative to the head; it is roughly one-eighth the size of the head; it is located above and to the right of the head's center. In this schema, the relationships—size, shape, and orientation—are constant, and the nodes—eye, nose, mouth—are "placeholders" whose exact nature varies from case to case. Eye color, for example, is not specified in the face schema. But eyes are always above the nose. As in most cases, it is therefore the schema's structure, determined by the links, rather than characteristics of individual nodes that is encoded and against which new information is compared.

5.3.1.4. Schema as Dynamic Structure. A schema is **not immutable.** As we learn new information, either from instruction or from day-to-day interaction with the environment, our memory and understanding of our world will change. Schema theory proposes that our knowledge of the world is constantly interpreting new experience and adapting to it. These processes, which Piaget (1968) has called *assimilation* and *accommodation,* and which Thorndyke and Hayes-Roth (1979) have called *bottom-up* and *top-down* processing, interact dynamically in an attempt to achieve cognitive equilibrium without which the world would be a tangled blur of meaningless experiences. The process works like this: (1) When we encounter a new object, experience, or piece of information, we attempt to match its features and structure (nodes and links) to a schema in memory (bottom-up). On the basis of the success of this first attempt at matching, we construct a hypothesis about the identity of the object, experience, on information, on the basis of which we look for further evidence to confirm our identification (top-down). If further evidence confirms our hypothesis, we assimilate the experience to the schema. If it does not, we revise our hypothesis, thus accommodating to the experience.

Let us return to Palmer's (1975) "face" schema to illustrate. Palmer describes what happens when a person is shown a "face, " whose head consists of a watermelon, whose eyes are apples, whose nose is a pear, and whose mouth is a banana. At first glance, on the basis of structural cues, one interprets the picture as a face. However, this hypothesis is not borne out when confirming evidence is sought and a "fruit" schema (or perhaps "fruitface" schema) is hypothesized. Admittedly, this example is a little unusual. However, it brings home the importance of structure in schemata and illustrates the fact that accommodation of a schema to new information is often achieved by reconciling discrepancies between global and local features.

Learning takes place as schemata change, as they accommodate to new information in the environment, and as new information is assimilated by them. Rumelhart and Norman (1981) discuss important differences in the extent to which these changes take place. Learning takes place by accretion, by schema tuning, or by schema creation.

In the case of accretion, the match between new information and schemata is so good that the new information is simply added to an existing schema with almost no accommodation of the schema at all. A hiker might learn to recognize a golden eagle simply by matching it to an already-familiar bald eagle schema, noting only the absence of the former's white head and tail.

Schema tuning results in more radical changes in a schema. A child raised in the inner city might have formed a "bird" schema on the basis of seeing only sparrows and pigeons. The features of this schema might be: a size of between 3 and 10 inches, flying by flapping wings, found around and on buildings. This child's first sighting of an eagle would probably be confusing, and might lead to a misidentification as an airplane, which is bigger than 10 inches long and does not flap its wings. Learning, perhaps through instruction, that this creature was indeed a bird would lead to changes in the "bird" schema, to include soaring as a means of getting around, large size, and mountain habitat.

Rumelhart and Norman describe schema creation as occurring by analogy. Stretching the bind example to the limits of credibility, imagine someone from a country that has no birds but lots of bats for whom a "bird" schema does not exist. The creation of a bird schema could take place by temporarily substituting the features birds have in common with bats and then specifically teaching the differences. The danger, of course, is that a significant residue of bat features could persist in the bird schema, in spite of careful instruction. Analogies can therefore be misleading (Spiro, Feltovich, Coulson & Anderson, 1989) if they are not used with extreme care.

5.3.1.5. Schema as Context. Not only does a schema serve as a repository of experiences. It provides a context that affects how we interpret new experiences and even directs our attention to particular sources of experience and information. From the time of Bartlett, schema theory has been developed largely from research in reading comprehension. And it is from this area of research that the strongest evidence comes for the decisive role of schemata in interpreting text.

The research design for these studies requires the activation of a well-developed schema to set a context, the presentation of a text that is often deliberately ambiguous, and a comprehension posttest. For example, Bransford and Johnson (1972) had subjects study a text that was so ambiguous as to be meaningless without the presence of an accompanying picture. Anderson, Reynolds, Schallert, and Goetz (1977) presented ambiguous stories to different groups of people. A story that could have been about weight lifting or a prison break was interpreted to be about weight lifting by students in a weight-lifting class, but in other ways by other students. Musicians interpreted a story that could have been about playing cards or playing music as if it were about music.

Neisser (1976) has argued that schemata not only determine interpretation but also affect people's anticipations of what they are going to find in the environment. Thus, in what Neisser calls a *perceptual cycle,* "anticipatory schemata" direct our exploration of the environment. Our exploration of the environment leads us to some sources of information rather than others. The information we find modifies our schemata, in ways we have already encountered, and the cycle repeats itself.

5.3.2 Schema Theory and Educational Technology

Schema theory has influenced educational technology in a variety of ways. For instance, the notion of activating a schema in order to provide a relevant context for learning finds a close parallel in Gagné, Briggs, and Wager's (1988) third instructional "event, " "stimulating recall of prerequisite learning." Reigeluth's (Reigeluth & Stein, 1983) "elaboration theory" of instruction consists of, among other things, prescriptions for the progressive refinement of schemata. The notion of a "generality, " which has persisted through the many stages of Merrill's instructional theory (Merrill, 1983, 1988; Merrill, Li & Jones, 1991), is close to a schema.

There are however three particular ways in which educational technology research has used schema theory (or at least some of the ideas it embodies, in common with other cognitive theories of representation). The first concerns the assumption, and attempts to support it, that schemata can be more effectively built and activated if the material that students encounter is somehow isomorphic to the putative structure of the schema. This line of research extends into the realm of cognitive theory's earlier attempts to propose and validate a theory of audiovisual (usually more visual than audio) education and concerns the role of pictorial and graphic illustration in instruction (Dale, 1946; Carpenter, 1953; Dwyer, 1972, 1978, 1987).

The second way in which educational technology has used schema theory has been to develop and apply techniques for students to use to impose structure on what they learn and thus make it more memorable. These techniques are referred to, collectively, by the term *information mapping.*

The third line of research consists of attempts to use schemata to represent information in a computer and thereby to enable the machine to interact with information in ways analogous to human assimilation and accommodation. This brings us to a consideration of the role of schemata, or "scripts" (Schank & Abelson, 1977) or "plans" (Minsky, 1975) in AI and "intelligent" instructional systems (see 19.2.3.1). The next sections examine these lines of research.

5.3.3 Schema-Message Isomorphism: Imaginal Encoding

There are two ways in which pictures and graphics can affect how information is encoded in schemata. Some research suggests that a picture is encoded directly as a mental image. This means that encoding leads to a schema that retains many of the properties of the message that the student saw, such as its spatial structure and the appearance of its features. Other research suggests that the picture or graphic imposes a structure on information first and that propositions about this structure rather than the structure itself are encoded. The schema therefore does not contain a mental image but information that allows an image to be created in the mind's eye when the schema becomes active. This and the next section examine these two possibilities.

Research into imaginal encoding is typically conducted within the framework of theories that propose two (at least) separate, though connected, memory systems (see 29.2.3). Paivio's (1983; Clark & Paivio, 1992) "dual coding" theory and Kulhavy's (Kulhavy, Lee & Caterino, 1985; Kulhavy, Stock & Caterino, 1994) "conjoint retention" theory are typical. Both theories assume that people can encode information as languagelike propositions on as picturelike mental images. This research has provided evidence that (1) pictures and graphics contain information that is not contained in text, and (2) that information shown in pictures and graphics is easier to recall because it is encoded in both memory systems, as propositions and as images, rather than just as propositions, which is the case when students read text. As an example, Schwartz and Kulhavy (1981) had subjects study a map while listening to a narrative describing the territory. Map subjects recalled more spatial information related to map features than nonmap subjects, while there was no difference between recall of the two groups on information not related to map features. In another study, Abel and Kulhavy (1989) found that subjects who saw maps of a territory recalled more details than subjects who read a corresponding text, suggesting that the map provided "second stratum cues" that made it easier to recall information.

5.3.4 Schema-Message Isomorphism: Structural Encoding

Evidence for the claim that graphics help students organize content by determining the structure of the schema in which it is encoded comes from studies that have examined the relationship between spatial presentations and cued or free recall. The assumption is that the spatial structure of the information on the page reflects the semantic structure of the information that gets encoded. For example, Winn (1980) used text with or without a block diagram to teach about a typical food web to high school subjects. Estimates of subjects' semantic structures representing the content were obtained from their free associations to words naming key concepts in the food web (e.g., *consumer herbivore).* It was found that the diagram significantly improved the closeness of the structure the students acquired to the structure of the content.

More recently, McNamara, Hardy, and Hirtle (1989) had subjects learn spatial layouts of common objects. Ordered trees, constructed from free-recall data, revealed hierarchical clusters of items that formed the basis for organizing the information in memory. A recognition test, in which targeted items were primed by items either within or outside the same cluster, produced response latencies that were faster for same-cluster items than for different-item clusters. The placement of an item in one cluster or another was determined, for the most part, by the spatial proximity of the items in the original layout.

In another study, McNamara (1986) had subjects study the layout of real objects placed in an area on the floor. The area was divided by low barriers into four quadrants of equal size. Primed recall produced response latencies suggesting that the physical boundaries imposed categories on the objects when they were encoded that overrode the effect of absolute spatial proximity. For example, recall reposes were slower to items physically close but separated by a boundary than two items further apart but within the same boundary. The results of studies like these have been the basis for recommendations about when and how to use pictures and graphics in instructional materials (Levin, Anglin & Carney, 1987; Winn, 1989b).

5.3.5 Schemata and Information Mapping

Strategies exploiting the structural isomorphism of graphics and knowledge schemata have also formed the basis for a variety of text- and information-mapping schemes aimed at improving comprehension (Armbruster & Anderson, 1982, 1984) and study skills (Dansereau et al., 1979; Holley & Dansereau, 1984). Research on the effectiveness of these strategies and its application is one of the best examples of how cognitive theory has come to be used by instructional designers.

The assumptions underlying all information-mapping strategies are that if information is well organized in memory, it will be better remembered and more easily associated with new information, and that students can be taught techniques exploiting the spatial organization of information on the page that make what they learn better organized in memory (see 24.7). We have already given examples of research that bears out the first of these assumptions. We turn now to research on the effectiveness of information-mapping techniques.

All information-mapping strategies (reviewed and summarized by Hughes, 1989) require students to learn ways to represent information, usually text, in spatially constructed diagrams. With these techniques, they construct diagrams that represent the concepts they are to learn as verbal labels often in boxes and that show interconcept relations as lines or arrows. The most obvious characteristic of these techniques is that students construct the information maps for themselves rather than studying diagrams created by someone else. In this way, the maps require students to process the information they contain in an effortful manner, while allowing a certain measure of idiosyncrasy in the ideas shown, both of which are attributes of effective learning strategies.

Some mapping techniques are radial, with the key concept in the center of the diagram and related concepts on arms reaching out from the center (Hughes, 1989). Other schemes are more hierarchical, with concepts placed on branches of a tree (Johnson, Pittelman & Heimlich, 1986).

Still others maintain the roughly linear format of sentences but use special symbols to encode interconcept relations, like equals signs or different kinds of boxes (Armbruster & Anderson, 1984). Some computer-based systems provide more flexibility by allowing "zooming" in on out on concepts to reveal subconcepts within them and by allowing users to introduce pictures and graphics from other sources (see 24.7; Fisher et al., 1990).

Regardless of format, information mapping has been shown to be effective. In some cases, information-mapping techniques have formed part of study skills curricula (Holley & Dansereau, 1984; Schewel, 1989). In other cases, the technique has been used to improve reading comprehension (Ruddell & Boyle, 1989) or for review at the end of a course (Fisher et al., 1990). Information mapping has been shown to be useful for helping students write about what they have read (Sinatra, Stahl-Gemake & Morgan, 1986) and works with disabled readers as well as with normal ones (Sinatra, Stahl-Gemake & Borg, 1986). Information mapping has proved to be a successful technique in all of these tasks and contexts, showing it to be remarkably robust.

Information mapping can, of course, be used by instructional designers (Jonassen, 1991, 1996; Jonassen, Bersner & Yacci, 1993). In this case, the technique is used not so much to improve comprehension as to help designers understand the relations among concepts in the material they are working with. Often, understanding such relations makes strategy selection more effective. For example, a radial outline based on the concept "zebra" (Hughes, 1989) shows, among other things, that a zebra is a member of the horse family and also that it lives in Africa on the open grasslands. From the layout of the radial map, it is clear that membership of the horse family is a different kind of interconcept relation than the relation with Africa and grasslands. The designer will therefore be likely to organize the instruction so that a zebra's location and habitat are taught together and not at the same time as the zebra's place in the mammalian taxonomy is taught. We will return to instructional designers' use of information mapping techniques in our discussion of cognitive objectives in section 5.5.

All of this seems to suggest that imagery-based and information-structuring strategies based on graphics have been extremely useful in practice. However, the whole idea of isomorphism between an information display outside the learner and the structure and content of a memory schema implies that information in the environment is mapped fairly directly into memory. As we have seen, this basic assumption of much of cognitive theory is currently being seriously challenged. The extent to which this challenge threatens the usefulness of using pictures and graphics in instruction remains to be seen.

5.3.6 Schemata and AI

Another way in which theories of representation have been used in educational technology is to suggest ways in which computer programs designed to "think" like people might represent information. Clearly, this application embodies the "computer models of mind" assumption that we looked at above (Boden, 1988).

The structural nature of schemata makes them particularly attractive to cognitive scientists working in the area of artificial intelligence. The reason for this is that they can be described using the same "language" that is used by computers and therefore provide a convenient link between human and artificial thought. The best examples are to be found in the work of Minsky (1975) and of Schank and his associates (Schank & Abelson, 1977). Here, schemata provide constraints on the meaning of information that the computer and the user share that make the interaction between them more manageable and useful. The constraints arise from only allowing what typically happens in a given situation to be considered. For example, certain actions and verbal exchanges commonly take place in a restaurant. You enter. Someone shows you to your table. Someone brings you a menu. After a while, the waiter comes back, and you order your meal. Your food is brought to you in a predictable sequence. You eat it in a predictable way. When you have finished, someone brings you the bill, which you pay. You leave. It is not likely (though not impossible, of course) that someone will bring you a basketball rather than the food you ordered. Usually, you will eat your food rather than sing to it. You use cash or a credit card to pay for your meal rather than offering a giraffe. In this way, the almost infinite number of things that can occur in the world are constrained to relatively few, which means that the machine has a better chance of figuring out what your words or actions mean.

Even so, schemata (or "scripts" as Schank [1984] calls them) cannot contend with every eventuality. This is because the assumptions about the world that are implicit in our schemata, and therefore often escape our awareness, have to be made explicit in scripts that are used in AI. Schank (1984) provides examples as he describes the difficulties encountered by TALE-SPIN, a program designed to write stories in the style of Aesop's fables.

> One day Joe Bear was hungry. He asked his friend Irving Bird where some honey was. Irving told him there was a beehive in the oak tree. Joe walked to the oak tree. He ate the beehive."

Here, the problem is that we know beehives contain honey, and while they are indeed a source of food, they are not themselves food but contain it. The program did not know this, non could it infer it. A second example, with Shank's own analysis, makes a similar point:

> Henry Ant was thirsty. He walked over to the river bank where his good friend Bill Bird was sitting. Henry slipped and fell in the river. He was unable to call for help. He drowned.
>
> This was not the story that TALE-SPIN set out to tell. [...] Had TALE-SPIN found a way for Henry to call to Bill for help, this would have caused Bill to try to save him. But the program had a rule that said that being in water prevents speech. Bill was not asked a direct question, and there was no way for any character to just happen to notice something. Henry drowned because the program knew that that's what happens when a character that can't swim is immersed in water (1984, p. 84).

The rules that the program followed, leading to the sad demise of Henry, are rules that normally apply. People do not usually talk when they're swimming. However, in this case, a second rule should have applied, as we who understand a calling-for-help-while-drowning schema are well aware of.

The more general issue that arises from these examples is that people have extensive knowledge of the world that goes beyond any single set of circumstances that might be defined in a script. And human intelligence rests on the judicious use of this general knowledge. Thus, on the rare occasion that we do encounter someone singing to their food in a restaurant, we have knowledge from beyond the immediate context that lets us conclude the person has had too much to drink, or is preparing to sing a role at the local opera and is therefore not really singing to her food at all, or belongs to a cult for whom praising the food about to be eaten in song is an accepted ritual. The problem for the AI designer is therefore how much of this general knowledge to allow the program to have? Too little, and the correct inferences cannot be made about what has happened when there are even small deviations from the norm. Too much, and the task of building a production system that embodies all the possible reasons for something to occur becomes impossibly complex.

It has been claimed that AI has failed (Dreyfus & Dreyfus, 1986) because "intelligent" machines do not have the breadth of knowledge that permits human reasoning. A current project called "Cyc" (Guha & Lenat, 1991; Lenat, Guha, Pittman, Pratt & Shepherd, 1990) has as its goal to imbue a machine with precisely the breadth of knowledge that humans have. Over a period of years, programmers will have worked away at encoding an impressive number of facts about the world. If this project is successful, it will be testimony to the usefulness of general knowledge of the world for problem solving and will confirm the severe limits of a "schema" or "script" approach to AI. It may also suggest that the schema metaphor is misleading. Maybe people do not organize their knowledge of the world in clearly delineated structures. A lot of thinking is "fuzzy, " and the boundaries among schemata are permeable and indistinct.

5.3.7 Mental Models

Another way in which theories of representation have influenced research in educational technology is through psychological and human factors research on mental models. A mental model, like a schema, is a putative structure that contains knowledge of the world. For some, mental models and schemata are synonymous. However, there are two properties of mental models that make them somewhat different from schemata. Mayer (1992, p. 431) identifies these as (1) representations of objects in whatever the model describes and (2) descriptions of how changes in one object effect changes in another. Roughly speaking, a mental model is broader in conception than a schema because it specifies causal actions among objects that take place within it. However, you will find any number of people who disagree with this distinction.

The term *envisionment* is often applied to the representation of both the objects and the causal relations in a mental model (DeKleer & Brown, 1981; Strittmatter & Seel, 1989). This term draws attention to the visual metaphors that often accompany discussion of mental models. When we use a mental model, we "see" a representation of it in our "mind's eye." This representation has spatial properties akin to those we notice with our biological eye. Some objects are "closer to" some than to others. And from seeing changes in our mind's eye in one object occurring simultaneously with changes in another, we infer causality between them. This is especially true when we consciously bring about a change in one object ourselves. For example, Steinberg and Weil (1980) gave subjects such problems to solve as: "If A is bigger than B and C is bigger than A, who is the smallest?" Subjects who changed the representation of the problem by placing the objects A, B, and C in a line from tallest to shortest were most successful in solving the problem, because envisioning it in this way allowed them simply to "see" the answer. Likewise, envisioning what happens in an electrical circuit that includes an electric bell (DeKleer & Brown, 1981) allows someone to come to understand how it works. In short, a mental model can be "run" like a film or computer program and watched in the mind's eye while it is running. You may have observed world-class skiers "running" their model of a slalom course, eyes closed, body leaning into each gate, before they make their run.

The greatest interest in mental models by educational technologists lies in ways of getting learners to create good ones. This implies, as in the case of schema creation, that instructional materials and events act with what learners already understand in order to construct a mental model that the student can use to develop understanding. Just how instruction affects mental models has been the subject of considerable research, summarized by Gentner and Stevens (1983), Mayer (1989a), and Rouse and Morris (1986), among others. At the end of his review, Mayer lists seven criteria that instructional materials should meet to induce mental models that are likely to improve understanding. (Mayer refers to the *materials,* typically illustrations and text, as "conceptual models" that describe in graphic form the objects and causal relations among them.) A good model is: Complete—it contains all the objects, states, and actions of the system; Concise—it contains just enough detail; Coherent—it makes "intuitive sense"; Concrete—it is presented at an appropriate level of familiarity; Conceptual—it is potentially meaningful; Correct—the objects and relations in it correspond to actual objects and events; and Considerate—it uses appropriate vocabulary and organization.

If these criteria are met, then instruction can lead to the creation of models that help students understand systems and solve problems arising from the way the systems work. For example, Mayer (1 989b) and Mayer and Gallini (1990) have demonstrated that materials, conforming to these criteria, in which graphics and text work together to illustrate both the objects and causal relations in systems (hydraulic drum brakes, bicycle pumps) were effective at promoting understanding. Subjects were able to answer questions requiring them to draw inferences from their mental models of the system using information they had not been explicitly taught. For instance, the answer (not explicitly taught) to the question "Why do brakes get hot?" can be found only in an understanding of the causal relations among the pieces of a brake system. A correct answer implies that an accurate mental model has been constructed.

A second area of research on mental models in which educational technologists are now engaging arises from a belief that interactive multimedia systems are effective tools for model building (Hueyching & Reeves, 1992; Kozma, Russell, Jones, Marx & Davis, 1993; Seel & Dorr, 1994). For the first time, we are able, with reasonable ease, to build instructional materials that are both interactive and that, through animation, can represent the changes of state and causal actions of physical systems. Kozma et al. describe a computer system that allows students to carry out simulated chemistry experiments. The graphic component of the system (which certainly meets Mayer's criteria for building a good model) presents information about changes of state and causality within a molecular system. It "corresponds to the molecular-level mental models that chemists have of such systems" (Kozma et al., 1993, p. 16). Analysis of constructed student responses and of think-aloud protocols have demonstrated the effectiveness of this system at helping students construct good mental models of chemical reactions. Byrne, Furness, and Winn (1995) describe a virtual environment in which students learn about atomic and molecular structure by building atoms from their subatomic components. The most successful treatment for building mental models was a highly interactive one.

5.3.8 Mental Representation and the Development of Expertise

The knowledge we represent as schemata or mental models changes as we work with it over time. It becomes much more readily accessible and useable, requiring less conscious effort to use it effectively. At the same time, its own structure becomes more robust, and it is increasingly internalized and automatized. The result is that its application becomes relatively straightforward and automatic, and frequently occurs without our conscious attention. When we drive home after work, we do not have to think hard about what to do or where we are going. It is important in the research that we shall examine below that this process of "knowledge compilation and translation" (Anderson, 1983) is a slow process. One of the biggest oversights in our field has occurred when instructional designers have assumed that task analysis should describe the behavior of experts rather than novices, completely ignoring the fact that expertise develops in stages and that novices cannot simply "get there" in one jump.

Out of the behavioral tradition that continues to dominate a great deal of thinking in educational technology comes the assumption that it is possible for mastery to result from instruction. In mastery learning, the only instructional variable is the time required to learn something. Therefore, given enough time, anyone can learn anything. The evidence that this is the case is compelling (Bloom, 1984, 1987; Kulik, 1990a, b). However, "enough time" typically comes to mean the length of a unit, module, or semester, and "mastery" means mastery of performance, not of high-level skills such as problem solving.

There is a considerable body of opinion that expertise arises from a much longer exposure to content in a learning environment than that implied in the case of mastery learning. Labouvie-Vief (1990) has suggested that wisdom arises during adulthood from processes that represent a fourth "stage" of human development, beyond Piaget's traditional three. Achieving a high level of expertise in chess (Chase & Simon, 1973) or in the professions (Schon, 1983, 1987) takes many years of learning and applying what one has learned. This implies that learners move through stages on their way from novicehood to expertise, and that, as in the case of cognitive development (Piaget & Inhelder, 1969), each stage is a necessary prerequisite for the next and cannot be skipped. In this case, expertise does not arise directly from instruction. It may start with some instruction, but it develops fully only with maturity and experience on the job (Lave & Wenger, 1991).

An illustrative account of the stages a person goes through on the way to expertise is provided by Dreyfus and Dreyfus (1986). The stages are: novice, advanced beginner, competence, proficiency, and expertise. Dreyfus and Dreyfus's examples are exceptionally useful in clarifying the differences between stages. The following few paragraphs are therefore based on their narrative (1986, pp. 21—35).

Novices learn objective and unambiguous facts and rules about the area that they are beginning to study. These facts and rules are typically learned out of context. For example, beginning nurses learn how to take a patient's blood pressure and are taught rules about what to do if the reading is normal, high, or very high. However, they do not yet necessarily understand what blood pressure really indicates or why the actions specified in the rules are necessary or how they affect the patient's recovery. In a sense, the knowledge they acquire is "inert" (Cognition and Technology Group at Vanderbilt, 1990) in that, though it can be applied, it is applied blindly and without a context or rationale.

Advanced beginners continue to learn more objective facts and rules. However, with their increased practical experience, they also begin to develop a sense of the larger context in which their developing knowledge and skill operate. Within that context, they begin to associate the

objective rules and facts they have learned with particular situations they encounter on the job. Their knowledge becomes "situational" or "contextualized." For example, student nurses begin to recognize patients' symptoms by means that cannot be expressed in objective, context-free rules. The way a particular patient's breathing sounds may be sufficient to indicate that a particular action is necessary. However, the sound itself cannot be described objectively, nor can recognizing it be learned anywhere except on the job.

As the student moves into competence and develops further sensitivity to information in the working environment, the number of context-free and situational facts and rules begins to overwhelm the student. The situation can be managed only when the student learns effective decision-making strategies. Student nurses at this stage often appear to be unable to make decisions. They are still keenly aware of the things they have been taught to look out for and the procedures to follow in the maternity ward. However, they are also now sensitive to situations in the ward that require them to change the rules and procedures. They begin to realize that the baby screaming its head off requires immediate attention even if to give that attention is not something set down in the rules. They are torn between doing what they have been taught to do and doing what they sense is more important at that moment. And often they dither, as Dreyfus and Dreyfus put it, ". . . like a mule between two bales of hay" (1986, p. 24).

Proficiency is characterized by quick, effective, and often unconscious decision making. Unlike the merely competent student, who has to think hand about what to do when the situation is at variance with objective rules and prescribed procedures, the proficient student easily grasps what is going on in any situation and acts, as it were, automatically to deal with whatever arises. The proficient nurse simply notices that a patient is psychologically ready for surgery, without consciously weighing the evidence.

With expertise comes the complete fusion of decision making and action. So completely is the expert immersed in the task, and so complete is the expert's mastery of the task and of the situations in which it is necessary to act, that ". . . When things are proceeding normally, experts don't solve problems and don't make decisions; they do what normally works" (Dreyfus & Dreyfus, 1986, pp. 30—31). Clearly, such a state of affairs can arise only after extensive experience on the job. With such experience comes the expert's ability to act quickly and correctly from information without needing to analyze it into components. Expert radiologists can perform accurate diagnoses from X rays by matching the pattern formed by light and dark areas on the film to patterns they have learned over the years to be symptomatic of particular conditions. They act on what they see as a whole and do not attend to each feature separately. Similarly, early research on expertise in chess (Chase & Simon, 1973) revealed that grand masters rely on the recognition of patterns of pieces on the chessboard to guide their play and engage in less in-depth analysis of situations than merely proficient players. Expert nurses sometimes sense that a patient's situation has become critical without there being any objective evidence, and, although they cannot explain why, they are usually correct.

A number of things are immediately clean from his account of the development of expertise. The first is that any student must start by learning explicitly taught facts and rules even if the ultimate goal is to become an expert who apparently functions perfectly well without using them at all. Spiro et al. (1992) claim that learning by allowing students to construct knowledge only works for "advanced knowledge" that assumes the basics have already been mastered.

Second, though, is the observation that students begin to learn situational knowledge and skills as early as the "advanced beginner" stage. This means that the abilities that appear intuitive, even magical, in experts are already present in embryonic form at a relatively early stage in a student's development. The implication is that instruction should foster the development of situational, nonobjective knowledge and skill as early as possible in a student's education. This conclusion is corroborated by the study of situated learning (Brown, Collins & Duguid, 1989) and apprenticeships (Lave & Wenger, 1991) in which education is situated in real-world contexts from the start (see also 7.4.4, 20.3).

Third is the observation that as students becomes more expert, they are *less* able to rationalize and articulate the reasons for their understanding of a situation and for their solutions to problems. Instructional designers and knowledge engineers generally are acutely aware of the difficulty of deriving a systematic and objective description of knowledge and skills from an expert as they go about content or task analyses. Experts just do things that work and do not engage in specific on describable problem solving. This also means that assessment of what students learn as they acquire expertise becomes increasingly difficult and eventually impossible by traditional means, such as tests. Tacit knowledge (Polanyi, 1962) is extremely difficult to measure.

Finally, we can observe that what educational technologists spend most of their time doing—developing explicit and measurable instruction—is only relevant to the earliest step in the process of acquiring expertise. There are two implications of this. First, we have, until recently, ignored the potential of technology to help people learn anything except objective facts and rules. And these, in the scheme of things we have just described, though necessary, are intended to be quickly superseded by other kinds of knowledge and skills that allow us to work effectively in the world. We might conclude that instructional design, as traditionally conceived, has concentrated on creating nothing more than training wheels for learning and acting that are to be jettisoned for more important knowledge and skills as quickly as possible. The second implication is that by basing instruction on the knowledge and skills of experts, we have completely ignored the protracted development that has led up to that state. The student must go through a number of qualitatively different stages that come between novicehood and expertise, and can no more jump directly from stage 1 to stage 5 than a child can go from Piaget's preoperational stage of development to formal operations without passing through the intervening developmental steps. If we try to teach the skills of the expert directly to novices, we shall surely fail.

The Dreyfus and Dreyfus account is by no means the only description of how people become experts. Non is it to any great extent given in terms of the underlying psychological processes that enable it to develop, In the next paragraphs, we look briefly at more specific accounts of how expertise is acquired, focusing on two cognitive processes: automaticity and knowledge organization.

5.3.8.1. Automaticity. From all accounts of expertise, it is clear that experts still do the things they learned to do as novices, but, more often than not, they do them without thinking about them. The automatization of cognitive and motor skills is a step along the way to expertise that occurs in just about every explanation of the process. By enabling experts to function without deliberate attention to what they are doing, automaticity frees up cognitive resources that the expert can then bring to bean on problems that arise from unexpected and hitherto unexperienced events, as well as allowing more attention to be paid to the more mundane though particular characteristics of the situation. This has been reported to be the case for such diverse skills as learning psychomotor skills (Romiszowski, 1993), developing skill as a teacher (Leinhart, 1987), typing (Larochelle, 1982), and the interpretation of X rays (Lesgold et al., 1988).

Automaticity occurs as a result of overlearning (Shiffrin & Schneider, 1977). Under the mastery learning model (Bloom, 1984), a student keeps practicing and receiving feedback, iteratively, until some predetermined criterion has been achieved. At that point, the student is taught and practices the next task. In the case of overlearning, the student continues to practice after attaining mastery, even if the achieved criterion is 100% performance. The more students practice using knowledge and skill beyond just mastery, the more fluid and automatic their skill will become. This is because practice leads to discrete pieces of knowledge and discrete steps in a skill becoming fused into larger pieces, or "chunks." Anderson (1983, 1986) speaks of this process as "knowledge compilation" in which declarative knowledge becomes procedural. Just as a computer compiles statements in a computer language into a code that will actually run, so, Anderson claims, the knowledge that we first acquire as explicit assertions of facts or rules is "compiled" by extended practice into knowledge and skill that will run on its own without our deliberately having to attend to them. Likewise, Landa (1983) describes the process whereby knowledge is transformed first into skill and then into ability through practice. At an early stage of learning something, we constantly have to refer to statements in order to be able to think and act. Fluency only comes when we no longer have to refer explicitly to what we know. Further practice will turn skills into abilities that are characterized by being our natural, intuitive manner of doing things.

5.3.8.2. Knowledge Organization. We mentioned briefly above that experts appear to solve problems by recognizing and interpreting the patterns in bodies of information, not by breaking down the information into its constituent parts. If automaticity corresponds to the "cognitive process" side of expertise, then knowledge organization is the equivalent of "mental representation" of knowledge by experts.

There is considerable evidence that experts organize knowledge in qualitatively different ways from novices. It appears that the chunking of information that is characteristic of experts' knowledge leads them to consider patterns of information when they are required to solve problems rather than improving the way they search through what they know to find an answer. For example, chess masters are fan less affected by time pressure than lesser players (Calderwood, Klein & Crandall, 1988). Requiring players to increase the number of moves they make in a minute will obviously reduce the amount of time they have to search through what they know about the relative success of potential moves. However, pattern recognition is a much more instantaneous process and will therefore not be as affected by increasing the number of moves per minute. Since masters were less affected than less-expert players by increasing the speed of a game of chess, it seems that they use pattern recognition rather than search as their main strategy.

Charness (1989) reported changes in a chess player's strategies over a period of 9 years. There was little change in the player's skill at searching through potential moves, However, there were noticeable changes in recall of board positions, evaluation of the state of the game, and chunking of information, all of which, Charness claims, are pattern-related rather than search-related skills. Moreover, Saariluoma (1990) reported, from protocol analysis, that strong chess players in fact engaged in *less* extensive search than intermediate players, concluding that what is searched is more important than how deeply the search is conducted.

It is important to note that some researchers (Patel & Groen, 1991) explicitly discount pattern recognition as the primary means by which some experts solve problems. Also, in a study of expert X-ray diagnosticians, Lesgold et al. (1988) propose that experts' knowledge schemata are developed through "deeper" generalization and discrimination than novices' . It is important to note that in cases where pattern recognition is not taken to be the key to expert performance, studies nonetheless supply evidence of qualitative differences in the nature and use of knowledge between experts and novices.

5.3.9 Summary

In this section we have seen that theories of mental representation have influenced research in educational technology in a number of ways. Schema theory, or something very much like it, is basic to just about all cognitive research on representation. And schema theory is centrally implicated in what we call *message design.* Establishing predictability and control over what appears in instructional materials and how the depicted information is represented has been high on the research agenda. So it has been of prime importance to discover (a) the nature of mental schemata and (b) how changing messages affects how schemata change or are created.

Mental representation is also the key to information-mapping techniques that have proved to help students understand and remember what they read. Here, however, the emphasis is on how the relations among objects and events are encoded and stored in memory and less on how the objects and events are shown. Also, these interconcept relations are often metaphorical. Within the graphical conventions of information maps—hierarchies, radial outlines, and so on—"above, " "below, " "close to, " and "far from" use the metaphor of space to convey semantic, not spatial, structure (see Winn & Solomon, 1991, for research on these "metaphorical" conventions). Nonetheless, the supposition is that representing these relations in some kind of structure in memory improves comprehension and recall.

The construction of schemata as the basis for computer reasoning has not been entirely successful. This is largely because computers are literal minded and cannot draw on general knowledge of the world outside the scripts they are programmed to follow. The results of this, for storywriting at least, are often whimsical and humorous. However, some would claim that the broader implication is that AI is impossible to attain.

Mental model theory has a lot in common with schema theory. However, studies of comprehension and transfer of changes of state and causality in physical systems suggest that well-developed mental models can be "envisioned" and "run" as students seek answers to questions. The ability of multimedia computer systems to show the dynamic interactions of components suggests that this technology has the potential for helping students develop models that represent the world in accurate and accessible ways.

The way in which mental representation changes with the development of expertise has perhaps received less attention from educational technologists than it should. This is partly because instructional prescriptions and instructional design procedures (particularly the techniques of task analysis) have not taken into account the stages a novice must go through on the way to expertise, each of which requires the development of qualitatively different forms of knowledge. This is an area to which educational technologists could profitably devote more of their attention.

5.4 MENTAL PROCESSES

The second major body of research in cognitive science has sought to explain the mental processes that operate on the representations we construct of our knowledge of the world. Of course, it is not possible to separate our understanding, nor our discussion, of representations and processes. Indeed, the sections on mental models and expertise made this abundantly clear! However, a body of research exists that has tended to focus more on process than representation. It is to this that we now turn.

All of what follows in this section rests on the assumption that cognitive actions operate on mental representations. As the cognitive actions occur, mental representations change in some way. And changes in mental representations mean changes in our knowledge of the world, which we call *learning*. By and large, we can therefore think of three families of cognitive processes, each bringing about its own kind of change in mental representation, and therefore resulting in its own kind of learning. The distinctions, predictably, are not always clean. But the three kinds of mental processes have to do with (1) information processing, (2) symbol manipulation, and (3) knowledge construction. We shall examine each of these in turn.

5.4.1 Information-Processing Accounts of Cognition

As we have seen, one of the basic tenets of cognitive theory is that information that is present in an instructional stimulus is acted on by a variety of mediating variables before the student produces a response. Information-processing accounts of cognition describe stages that information moves through in the cognitive system and suggests processes that operate at each step. We therefore begin this section with a general account of information processing in human beings. This account sets the stage for our consideration of cognition as symbol manipulation and as knowledge construction.

Although the rise of information-processing accounts of cognition cannot be ascribed uniquely to the development of the computer, the early cognitive psychologists' descriptions of human thinking use distinctly computerlike terms. Like computers, people were supposed to take information from the environment into "buffers, " to "process" it before "storing it in memory." Information-processing models describe the nature and function of putative "units" within the human perceptual and cognitive systems, and how they interact. They trace their origins to Atkinson and Shiffrin's (1968) model of memory, which was the first to suggest that memory consisted of a sensory register, a long-term and a short-term store. According to Atkinson and Shiffrin's account, information is registered by the senses and then placed into a short-term storage area. Here, unless it is worked with in a "rehearsal buffer, " it decays after about 15 seconds. If information in the short-term store is rehearsed to any significant extent, it stands a chance of being placed into the long-term stone, where it remains more or less permanently. With no more than minor changes, this model of human information processing has persisted in the instructional technology literature (R. Gagné, 1974; E. Gagné, 1985) and in recent ideas about long-term and short-term, or working, memory (Gagné & Glaser, 1987). The importance that every instructional designer gives to practice stems from the belief that rehearsal improves the chance of information passing into long-term memory.

A major problem that this approach to explaining human cognition pointed to was the relative inefficiency of human beings at information processing. This is to be a result of the limited capacity of working memory to roughly seven (Miller, 1956) or five (Simon, 1974) pieces of information at one time. (E. Gagné [1985, p. 13] makes an interesting comparison between a computer's and a person's capacity to process information. The computer wins handily. However, human capacity to be creative, to imagine, and to solve complex problems does not enter into the equation.) It therefore became necessary to modify the basic model to account for these observations. One modification arose from studies like those of Shiffrin and Schneider (1977) and Schneider and Shiffrin (1977). In a series of memory experiments, these researchers demonstrated that, with sufficient rehearsal, people automatize what they have learned so that what was originally a number of discrete items become one single "chunk" of information. With what is referred to as "overlearning, " the limitations of working memory can be overcome. The notion of chunking information in order to make it possible for people to remember collections of more than five things has become quite prevalent in the information-processing literature (see Anderson, 1983). And rehearsal strategies intended to induce chunking became part of the standard repertoire of tools used by instructional designers.

Another problem with the basic information-processing account arose from research on memory for text in which it was demonstrated that people remembered the ideas of passages rather than the text itself (Bransford & Franks, 1971; Bransford & Johnson, 1972). This suggested that what was passed from working memory to long-term memory was not a direct representation of the information in short-term memory but a more abstract representation of its meaning. These abstract representations are, of course, schemata, which we discussed at some length earlier. Schema theory added a whole new dimension to ideas about information processing. So fan, information-processing theory assumed that the driving force of cognition was the information that was registered by the sensory buffers—that cognition was data driven, or bottom-up. Schema theory proposed that information was, at least in part, top-down. This meant, according to Neisser (1976), that cognition is driven as much as by what we know as by the information we take in at a given moment. In other words, the contents of long-term memory play a large part in the processing of information that passes through working memory. For instructional designers, it became apparent that strategies were required that guided top-down processing by activating relevant schemata and aided retrieval by providing the correct context for recall. The "elaboration theory of instruction" (Reigeluth & Stein, 1983; Reigeluth & Curtis, 1987) achieves both of these ends (see 18.4.3). Presenting an epitome of the content at the beginning of instruction activates relevant schemata. Providing synthesizers at strategic points during instruction helps students remember, and integrate, what they have learned up to that point.

Bottom-up, information-processing approaches have recently regained ground in cognitive theory as the result of the recognition of the importance of preattentive perceptual processes (Marr, 1982; Arbib & Hanson, 1987; Boden, 1988; Treisman, 1988; Pomerantz, Pristach & Carlson, 1989). Our overview of cognitive science, mentioned before, described computational approaches to cognition. In this return to a bottom-up approach, however, we can see marked differences from the bottom-up, information-processing approaches of the 60s and 70s. Bottom-up processes are now clearly confined within the barrier of what Pylyshyn (1984) called *cognitive impenetrability.* These are processes over which we can have no attentive, conscious, effortful control. Nonetheless, they impose a considerable amount of organization on the information we receive from the world. In vision, for example, it is likely that all information about the organization of a scene, except for some depth cues, is determined preattentively (Marr, 1982). What is more, preattentive perceptual structure predisposes us to make particular interpretations of information, top-down (Owens, 1985a, 1985b; Duong, 1994). In other words, the way our perception processes information determines how our cognitive system will process it. Subliminal advertising works!

Although we still talk rather glibly about short-term and long-term memory and use rather loosely other terms that come from information-processing models of cognition, information-processing theories have matured considerably since they first appeared in the late 50s. The balance between bottom-up and top-down theories, achieved largely within the framework of computational theories of cognition, offers researchers a good conceptual framework within which to design and conduct studies. Equally, instructional designers who are serious about bringing cognitive theory into educational technology will find in this latest incarnation of information-processing theory an empirically valid and rationally tenable basis for making decisions about instructional strategies.

5.4.2 Cognition as Symbol Manipulation

How is information that is processed by the cognitive system represented by it? One very popular answer is as symbols.” This notion lies close to the heart of cognitive science and, as we saw in the very first section of this chapter, it is also the source of some of the most virulent attacks on cognitive theory (Clancey, 1993). The idea is that we think by mentally manipulating symbols that are representations, in our mind’s eye, of referents in the real world. There is a direct mapping between objects and actions in the external world and the symbols we use internally to represent them. Our manipulation of these symbols places them into new relationships with each other, allowing new insights into objects and phenomena. Our ability to reverse the process by means of which the world was originally encoded as symbols therefore allows us to act on the real world in new and potentially more effective ways.

We need to consider both how well people can manipulate symbols mentally and what happens as a result. The clearest evidence for people’s ability to manipulate symbols in their “mind’s eye” comes from Kosslyn’s (1985) studies of mental imagery. Kosslyn’s basic research paradigm was to have his subjects create a mental image and then to instruct them directly to change it in some way, usually by “zooming” in and out on it. Evidence for the success of his subjects at doing this was found in their ability to answer questions about properties of the imaged objects that could only be inspected as a result of such manipulation.

The work of Shepard and his colleagues (Shepard & Cooper, 1982) represents another “classical” case of our ability to manipulate images in our mind’s eye. The best known of Shepard’s experimental methods is as follows. Subjects are shown two three-dimensional solid figures seen from different angles. The figures may be the same or different, The subjects are asked to judge whether the figures are the same or different. In order to make the judgment, it is necessary to rotate mentally one of the figures in three dimensions in an attempt to orient it to the same position as the target, so that a direct comparison may be made. Shepard consistently found that the time it took to make the judgment was almost perfectly correlated with the number of degrees through which the figure had to be notated, suggesting that the subject was rotating it in real time in the mind’s eye.

Finally, Salomon (1979) speaks more generally of “symbol systems” and of people’s ability to internalize them and use them as “tools for thought.” In an early experiment (Salomon, 1974), he had subjects study paintings in one of the following three conditions: (a) A film showed the entire picture, zoomed in on a detail, and zoomed out again, for a total of 80 times. (b) The film cut from the whole picture directly to the detail without the transitional zooming. (c) The film showed just the whole picture. In a posttest of cue attendance, in which subjects were asked to write down as many details as they could from a slide of another picture, low-ability subjects performed better if they were in the “zooming” group. High-ability subjects did better if they just saw the entire picture. Salomon concluded that zooming in and out on details, which is a symbolic element in the symbol system of film, television, and any form of motion picture, modeled for the low-ability subjects a strategy for cue attendance that they could execute for themselves cognitively. This was not necessary for the high-ability subjects. Indeed, there was evidence that modeling the zooming strategy reduced performance of high-ability subjects because it got in the way of mental processes that were activated without prompting. Bovy (1983) found results similar to Salomon’s using “irising” rather than zooming. A similar interaction between ability and modeling was reported by Winn (1986) for serial and parallel pattern-recall tasks.

Salomon has continued to develop the notion of internalized symbol systems serving as cognitive tools. Educational technologists have been particularly interested in his research on how the symbolic systems of computers can "become cognitive, " as he put it (Salomon, 1988). The internalization of the symbolic operations of computers led to the development of a word processor, called the "Writing Partner" (Salomon, Perkins & Globerson, 1991), that helped students write. The results of a number of experiments showed that interacting with the computer led the users to internalize a number of its ways of processing, which led to improved metacognition relevant to the writing task. Most recently (Salomon, 1993), this idea has evolved even further, to encompass the notion of distributing cognition among students and machines (and, of course, other students).

This research has had two main influences on educational technology. The first, derived from work in imagery of the kind reported by Kosslyn and Shepard, provided an attractive theoretical basis for the development of instructional systems that incorporate large amounts of visual material (Winn, 1980, 1982). The promotion and study of visual literacy (Dondis, 1973; Sless, 1981) is one manifestation of this activity. A number of studies have shown that the use of visual instructional materials can be beneficial for some students studying some kinds of content. For example, Dwyer (1972, 1978) has conducted an extensive research program on the differential benefits of different kinds of visual materials, and has generally reported that realistic pictures are good for identification tasks, line drawings for teaching structure and function, and so on. Explanations for these different effects rest on the assumption that different ways of encoding material facilitate some cognitive processes rather than others—that some materials are more effectively manipulated in the mind's eye for given tasks than others.

The second influence of this research on educational technology has been in the study of the interaction between technology and cognitive systems. Salomon's research, which we just described, is of course an example of this. The work of Papert and his colleagues at MIT's Media Lab is another important example. Papert (1983) began by proposing that young children can learn the "powerful ideas" that underlie reasoning and problem solving by working (perhaps *playing* is the more appropriate term) in a microworld over which they have control. The archetype of such a microworld is the well-known LOGO environment (see 24.5.1.3) in which the student solves problems by instructing a "turtle" to perform certain tasks. Learning occurs when the children develop problem definition and debugging skills as they write programs for the turtle to follow. Working with LOGO, children develop fluency in problem solving as well as specific skills, like problem decomposition and the ability to modularize problem solutions. Like Salomon's (1988) subjects, the children who work with LOGO (and in other technology-based environments [Harel & Papert, 1991]) internalize a lot of the computer's ways of using information and develop skills in symbol manipulation that they use to solve problems.

There is, of course, a great deal of research into problem solving through symbol manipulation that is not concerned particularly with technology. The work of Simon and his colleagues is central to this research. (See Klahr & Kotovsky's [1989] edited volume that pays tribute to his work.) It is based largely on the notion that human reasoning operates by applying rules to encoded information that manipulate the information in such a way as to reveal solutions to problems. The information is encoded as a "production system" that operates by testing whether the conditions of rules are true or not, and following specific actions if they are (see also 24.8.1). A simple example: "If the sum of an addition of a column of digits is greater than 10, then write down the right-hand integer and carry 1 to add to the next column." The "if …then structure is a simple production system in which a mental action is carried out (add 1 to the next column) if a condition is true (the number is greater than 10).

An excellent illustration is to be found in Larkin and Simon's (1987) account of the superiority of diagrams over text for solving certain classes of problems. Here, they develop a production system model of pulley systems to explain how the number of pulleys attached to a block, and the way in which they are connected, affects the amount of weight that can be raised by a given force. The model is quite complex. It is based on the idea that people need to search through the information presented to them in order to identify the conditions of a rule (e.g., if a rope passes over two pulleys between its point of attachment and a load, its mechanical advantage is doubled) and then compute the results of applying the production rule in those given circumstances. The two steps, searching for the conditions of the production rule and computing the consequences of its application, draw on cognitive resources (memory and processing) to different degrees. Larkin and Simon's argument is that diagrams require less effort to search for the conditions and to perform the computation, which is why they are so often more successful than text for problem solving.

It is easier to explain the symbol manipulation required to search for information and use it to compute the answer to a question with a simpler example. Winn, Li, and Schill (1991) conducted an empirical test of some aspects of Larkin and Simon's account using family trees rather than pulley systems. Subjects examined either family trees or statements about who was related to whom. They were given questions to answer about kinship, such as, "Is Mary Jack's second cousin?" The dependent measure of most interest was the speed at which subjects were able to answer the questions. Arguing that the information presented in the text required more cognitive manipulation than that provided by the family trees, from which answers could be obtained by simple inspection, it was expected that subjects seeing diagrams would be able to answer kinship questions quicker than those who saw text. This turned out to be the case.

These results, along with analysis of strategies that subjects used to find answers to the questions, supported the following interpretation. The text condition provided simple factual statements about who was whose parent, such as "Jack is Mary's parent; Jack is Edward's parent; Mary is Penny's parent   To answer a question from text, such as, "Is Amy Joseph's first cousin?", the subject has to read through the list until the first relevant piece of information was found, which in this case would be a statement about who Amy's parent was. That information had to be stoned in memory, while the second piece of information, about Joseph's parents, was sought and remembered. For first cousins, it was necessary to repeat this search-and-stone process twice more, to find who were the parents of Amy's and Joseph's parents, before all the conditions of the production could be satisfied. This required encoding and retrieval of at least four pieces of information, assuming the subject was 100% efficient. Next, the answer had to be computed from this information. Either the lineage of Amy and Joseph made them second cousins or it did not.

In the case of family trees, once the first person in the problem had been found, all that was necessary to do was to trace up and down the tree the required number of branches and read off the name at the end. Nothing had to be stored in memory, and no computations were required. This, of course, was only the case when kinship terms *(cousin, sibling)* and the conventions of family trees were known to subjects. When this was not the case, and subjects had to apply kinship rules explicitly, the advantage of the graphic was reduced. For example, in one experiment, some subjects worked with Chinese names and kinship terms defined for them in a rule. So the requirements of symbol manipulation to solve problems are removed when the conventions of the graphic representation are known. Interestingly, the most rapid responses were given by subjects, in the graphic condition, who were told no kinship rules at all. They simply used their knowledge that cousins are always on the same level of a family tree and did not examine parents at all.

This study, and Larkin and Simon's production system model that lay behind it, illustrate very well the symbol manipulation approach to theories of cognitive processing. In the case of both pulleys and families, subjects encode objects (pulleys, ropes, weights, people's names, and kinship) as symbols that they are required to store in memory and manipulate through comparisons, tracing relationships among them, and so on. When the symbols are represented as diagrams of pulley systems or family trees, relationships among them that are crucial to understanding the systems, and answering questions about them are made explicit by their relative placement on the page and by drawings of the links among them: ropes between pairs of pulleys, lines between names in the family tree. This makes the search for conditions of production rules much simpler and does not draw on memory at all. Computation consists of reading off the answer once all the conditions have been met. If, in addition, the graphic representation uses conventions with which the reader is familiar, search and computation can be short-circuited completely, making the task trivial by comparison.

Many other examples of symbol manipulation through production systems exist. In the area of mathematics education, the interested reader will wish to look at projects reported by Resnick (1976) and Greeno (1980) in which instruction makes it easier for students to encode and manipulate mathematical concepts and relations. Applications of Anderson's (1983) ACT* production system in intelligent computer-based tutors to teach geometry, algebra, and LISP are also illustrative (Anderson & Reiser, 1985; Anderson, Boyle & Yost, 1985).

For the educational technologist, the question arises of how to make symbol manipulation easier so that problems may be solved more rapidly and accurately. Larkin and Simon and Winn, Li, and Schill show that one way to do this is to show conceptual relationships by layout and links in a graphic. A related body of research concerns the relations between illustrations and text. (See summaries in Willows & Houghton, 1987; Houghton & Willows, 1987; Mandl & Levin, 1989; Schnotz & Kulhavy, 1994.) Central to this research is the idea that pictures and words can work together to help students understand information more effectively and efficiently. There is now considerable evidence that people encode information in one of two memory systems, a verbal system and an imaginal system. This "dual coding" (Paivio, 1983; Clark & Paivio, 1991) or "conjoint retention" (Kulhavy, Lee & Caterino, 1985) has two major advantages. The first is redundancy. Information that is hard to recall from one source is still available in the other. Second is the uniqueness of each coding system. As Levin, Anglin, and Carney (1987) have ably demonstrated, different types of illustration are particularly good at performing unique functions. Realistic pictures are good for identification, cutaways and line drawings for showing the structure or operation of things. Text is more appropriate for discursive and more abstract presentations.

Specific guidelines for instructional design have been drawn from this research, many presented in the summaries mentioned in the previous paragraph. Other useful sources are chapters by Mayer and by Winn in Fleming and Levie's (1993) volume on message design. The theoretical basis for these principles is by and large the facilitation of symbol manipulation in the mind's eye that comes from certain types of presentation.

However, as we saw at the beginning of this chapter, the basic assumption that we think by manipulating symbols that represent objects and events in the real world has been called into question (Clancey, 1993). There are a number of grounds for this criticism. The most compelling is that we do not carry around in our heads representations that are accurate "maps" of the world. Schemata, mental models, symbol systems, search, and computation are all metaphors that give a superficial appearance of validity because they predict behavior. However, the essential processes that underlie the metaphors are more amenable to genetic and biological than to psychological analysis. We are, after all, living systems that have evolved like other living systems. And our minds are embodied in our brains, which are organs just like any other. We shall leave the implications of this line of argument to those writing other chapters in this handbook. For now, we shall turn to a relatively uncontroversial and well-rooted corollary, that people construct knowledge for themselves rather than receiving it from someone else.

5.4.3 Cognition as Knowledge Construction

One result of the mental manipulation of symbols is that new concepts can be created. Our combining and recombining of mentally represented phenomena leads to the creation of new schemata that may or may not correspond to things in the real world. When this activity is accompanied by constant interaction with the environment in order to verify new hypotheses about the world, we can say that we are accommodating our knowledge to new experiences in the "classic" interactions described by Neisser (1976) and Piaget (1968), mentioned earlier. When we construct new knowledge without direct reference to the outside world, then we are perhaps at our most creative, conjuring from memories thoughts and expressions of it that are entirely novel.

When we looked at schema theory, we described Neisser's (1976) "perceptual cycle, " which describes how what we know directs how we seek information; how we seek information determines what information we get; and how the information we receive affects what we know. This description of knowledge acquisition provides a good account of how top-down processes, driven by knowledge we already have, interact with bottom-up processes, driven by information in the environment, to enable us to assimilate new knowledge and accommodate what we already know to make it compatible.

What arises from this description, which we did not make explicit earlier, is that the perceptual cycle and thus the entire knowledge acquisition process is centered on the person not the environment. Some (Duffy & Jonassen, 1992; Cunningham, 1992a; and Chapters 7 and 23 in this handbook) extend this notion to mean that the schemata a person constructs do not correspond in any absolute on objective way to the environment. A person's understanding is therefore built from that person's adaptations to the environment entirely in terms of the experience and understanding that the person has already constructed. There is no process whereby representations of the world are directly "mapped" onto schemata. We do not carry representational images of the world in our mind's eye. Semiotic theory, which has recently made an appearance on the educational stage (Cunningham, 1992b; Driscoll, 1990; Driscoll & Lebow, 1992) goes one step further, claiming that we do not apprehend the world directly at all. Rather, we experience it through the signs we construct to represent it. Nonetheless, if students are given responsibility for constructing their own signs and knowledge of the world, semiotic theory can guide the development and implementation of learning activities as Winn, Hoffman, and Osberg (1995) have demonstrated.

A thorough discussion of these ideas takes place in Chapters 7 and 23 and so will therefore not be pursued here. What is of relevance in this discussion of cognitive processes, however, is the notion that people do construct understanding for themselves in ways that are often idiosyncratic and that often defy expression to someone else. We all "know the world" in ways that differ, sometimes quite sharply, from other people. This idiosyncracy of knowledge has led some (Merrill, 1992) to react severely against instructional theories that aim at fostering construction of knowledge that varies among individuals on the grounds that some knowledge and skills must be acquired and expressed in a uniform manner. Idiosyncratic understanding of brain surgery or how to fly a plane could lead to disaster! However, one can reasonably make the case that some knowledge can be, indeed is best, constructed by individuals for themselves without the imposition of a right answer or a correct set of actions to follow as a result.

The significance of knowledge construction for educational technology lies in its marking a shift away from didactic, content-specific instruction to building environments that make it easy for students to construct their understanding of knowledge domains. Zucchermaglio (1993) describes "filled" and "empty" technologies. The former are instructional systems, like CAI and intelligent tutors, that consist of shells plus content. For example, Anderson, Boyle, and Yost's (1985) algebra tutor consists of a variety of generic components, found in any intelligent tutorial, such as the capability of constructing a student model, of making inferences, and so on (see chapters in Polson & Richardson, 1988). In addition, it contains a knowledge base about algebra from which the other components draw. On the other hand, empty technologies are shells that provide teachers and students with the capability of interacting with content, exploring information, and creating output, but which do not contain a predetermined knowledge base. An example is the "Bubble Dialogue" project (McMahon & O'Neil, 1993), which consists of a HyperCard stack that permits students to construct dialogues. The program allows students to write both the overt speech and the covert thoughts of the characters whose roles they play. Yet what the students write about is not prescribed, and the tool has been used for many purposes ranging from teaching writing to developing understanding about social problems.

If cognition is understood to involve the construction of knowledge by students, it is therefore essential that they be given the freedom to do so. This means that, within Spiro et al.'s (1992) constraints of "advanced knowledge acquisition in ill-structured domains, " instruction is less concerned with content, and sometimes only marginally so. Instead, educational technologists need to become more concerned with how students interact with the environments within which technology places them and with how objects and phenomena in those environments appear and behave. This requires educational technologists to read carefully in the area of human factors (for example, Ellis, 1993; Barfield & Furness, 1995) where a great deal of research exists on the cognitive consequences of human-machine interaction. It requires less emphasis on instructional design's traditional attention to task and content analysis. It requires alternative ways of thinking about (Winn, 1993b) and doing (Cunningham, 1992a) evaluation. In short, it is only through the cognitive activity that interaction with content engenders, not the content itself, that people can learn anything at all.

5.4.4 Summary

Information-processing models of cognition have had a great deal of influence on research and practice of educational technology. Instructional designers' day-to-day frames of reference for thinking about cognition, such as working memory and long-term memory, come directly from information-processing theory. The emphasis on rehearsal in many instructional strategies arises from the small capacity of working memory. Attempts to overcome for this problem have led designers to develop all manner of strategies to induce chunking. Information-processing theories of cognition continue to serve our field well.

Research into cognitive processes involved in symbol manipulation have been influential in the development of intelligent tutoring systems (Wenger, 1987), as well as in information-processing accounts of learning and instruction. The result has been that the conceptual bases for some (though not all) instructional theory and instructional design models have embodied a production system approach to instruction and instructional design (see Landa, 1983; Scandura, 1983; Merrill, 1992). To the extent that symbol manipulation accounts of cognition are being challenged, these approaches to instruction and instructional design are also challenged by association.

Accounts of learning through the construction of knowledge by students have been generally well accepted since the mid-70s and have served as the basis for a number of the assumptions educational technologists have made about how to teach. Attempts to set instructional design firmly on cognitive foundations (DiVesta & Rieber, 1987; Bonner, 1988; Tennyson & Rasch, 1988) reflect this orientation. We examine these in the next section.

5.5 COGNITIVE THEORY AND EDUCATIONAL TECHNOLOGY

Educational technology has for some time been influenced by developments in cognitive psychology. Up until now, we have focused mainly on research that has fallen outside the traditional bounds of our field. We have referred to sources in philosophy, psychology, computer science, and so on. In this section, we review the work of those who bean the title "educational technologist" who have been primarily responsible for bringing cognitive theory to our field. We are, again, of necessity selective, focusing on the applied side of our field, instructional design. We begin with some observations about what scholars consider design to be. We then examine the assumptions that underlay behavioral theory and practice at the time when instructional design became established as a discipline. We then argue that research in our field has helped the theory that designers use to make decisions about how to instruct keep up with developments in cognitive theory. However, design procedures have not evolved as they should have. We conclude with some implications about where design should go.

5.5.1 Theory, Practice, and Instructional Design

At the beginning of this chapter we noted that the discipline of educational technology hit its stride during the heyday of behaviorism. This historical fact was entirely fortuitous. Indeed, our field could have started equally well under the influence of Gestalt or of cognitive theory. However, the consequences of this coincidence have been profound and to some extent troublesome for our field. To explain why, we need to examine the nature of the relationship between theory and practice in our field. (Our argument is equally applicable to any discipline.)

The purpose of any applied field, such as educational technology, is to improve practice. The way in which theory guides that practice is through what Simon (1981) and Glaser (1976) call *design.* The purpose of design, seen this way, is to select the alternative from among several courses of action that will lead to the best results. Since these results may not be optimal, but the best one can expect given the state of our knowledge at any particular time, design works through a process Simon (1981) calls *satisficing.*

The degree of success of our activity as instructional designers relies on two things: first, the validity of our knowledge of effective instruction in a given subject domain and, second, the reliability of our procedures for applying that knowledge. Here is an example. We are given the task of writing a computer program that teaches the formation of regular English verbs in the past tense. To simplify matters, let us assume that we know the subject matter perfectly. As subject-matter specialists, we know a procedure for accomplishing the task: Add *ed* to the infinitive, and double the final consonant if it is immediately preceded by a vowel. Would our instructional strategy therefore be to do nothing more than show a sentence on the computer screen that says, "Add *ed* to the infinitive, and double the final consonant if it is immediately preceded by a vowel"? Probably not (though such a strategy might be all that is needed for students who already understand the meanings of *infinitive, vowel,* and *consonant).* If we know something about instruction, we will probably consider a number of other strategies as well. Maybe the students would need to see examples of correct and incorrect verb forms. Maybe they would need to practice forming the past tense of a number of verbs. Maybe they would need to know how well they were doing. Maybe they would need a mechanism that explained and corrected their errors. The act of designing our instructional computer program in fact requires us to choose from among these and other strategies the ones that are most likely to "satisfice" the requirement of constructing the past tense of regular verbs.

Knowing subject matter and something about instruction are therefore not enough. We need to know how to choose among alternative instructional strategies. Reigeluth (1983) has pointed the way. He observes that the instructional theory that guides instructional designers' choices is made up of statements about relations among the conditions, methods, and outcomes of instruction. When we apply prescriptive theory, knowing instructional conditions and outcomes leads to the selection of an appropriate method. For example, an instructional prescription might consist of the statement, "To teach how to form the past tense of regular English verbs (outcome) to advanced students of English who are familiar with all relevant grammatical terms and concepts (conditions), present them with a written description of the procedure to follow (method)." All the designer needs to do is learn a large number of these prescriptions and all is well.

There are a number of difficulties with this example, however. First, instructional prescriptions rarely, if at all, consist of statements at the level of specificity as the previous one about English verbs. Any theory gains power by its generality. This means that instructional theory contains statements that have a more general applicability, such as "to teach a procedure to a student with a high level of entering knowledge, describe the procedure." Knowing only a prescription at this level of generality, the designer of the verb program needs to determine whether the outcome of instruction is indeed a procedure—it could be a concept, or a rule, on require problem solving—and whether or not the students have a high level of knowledge when they start the program.

A second difficulty arises if the designer is not a subject-matter specialist, which is often the case faced by designers. In our example, this means that the designer has to find out that "forming the past tense of English verbs" requires adding *ed* and doubling the consonant.

Finally, the prescription itself might not be valid. Any instructional prescription that is derived empirically, from an experiment or from observation and experience, is always a generalization from a limited set of cases. It could be that the present case is an exception to the general rule. The designer needs to establish whether or not this is so.

These three difficulties point to the requirement that instructional designers know how to perform analyses that lead to the level of specificity required by the instructional task. We all know what these are. Task analysis permits the instructional designer to identify exactly what the student must achieve in order to attain the instructional outcome. Learner analysis allows the designer to determine the most critical of the conditions under which instruction is to take place. And the classification of tasks, described by task analysis, as facts, concepts, rules, procedures, problem solving, and so on links the designer's particular case to more general prescriptive theory. Finally, if the particular case the designer is working on is an exception to the general prescription, the designer will have to experiment with a variety of potentially effective strategies in order to find the best one, in effect inventing a new instructional prescription along the way.

Even from this simple example, it is clear that, in order to be able to select the best instructional strategies, the instructional designer needs to know *both* instructional theory *and* how to do task and learner analysis, to classify learning outcomes into some theoretically sound taxonomy, and to reason about instruction in the absence of prescriptive principles. Our field, then, like any applied field, provides to its practitioners both theory and procedures through which to apply the theory. These procedures are predominantly, though not exclusively, analytical.

Embedded in any theory are sets of assumptions that are amenable to empirical verification. If the assumptions are shown to be false, then the theory must be modified or abandoned as a paradigm shift takes place (Kuhn, 1970). The effects of these basic assumptions are clearest in the physical sciences. For example, the assumption in modern physics that it is impossible for the speed of objects to exceed that of light is so basic that, if it were to be disproved, the entire edifice of physics would come tumbling down. What is equally important is that the procedures for applying theory rest on the same set of assumptions. The design of everything from cyclotrons to radio telescopes relies on the inviolability of the "light barrier."

It would seem reasonable, therefore, that both the theory and procedures of instruction should nest on the same set of assumptions and, further, that should the assumptions of instructional theory be shown to be invalid, the procedures of instructional design should be revised to accommodate the paradigm shift. In the next section, we show that this was the case when instructional design established itself within our field within the behavioral paradigm. However, we do not believe that this is the case today.

5.5.2 The Legacy of Behaviorism

The most fundamental principle of behavioral theory is that there is a predictable and reliable link between a stimulus and the response it produces in a student. Behavioral instructional theory therefore consists of prescriptions for what stimuli to employ if a particular response is intended (see 2.2.1.3). The instructional designer can be reasonably certain that with the right sets of instructional stimuli all manner of learning outcomes can be attained. Indeed, behavioral theories of instruction can be quite intricate (Gropper, 1983) and can account for the acquisition of quite complex behaviors. This means that a basic assumption of behavioral theories of instruction is that human behavior is predictable. The designer assumes that if an instructional strategy, made up of stimuli, has had a certain effect in the past, it will probably do so again.

The assumption that behavior is predictable also underlies the procedures that instructional designers originally developed to implement behavioral theories of instruction (Andrews & Goodson, 1981; Gagné, Briggs & Wager 1988; Gagné & Dick, 1983). If behavior is predictable, then all the designer needs to do is to identify the subskills the student must master that, in aggregate, permit the intended behavior to be learned, and select the stimulus and strategy for its presentation that builds each subskill. In other words, task analysis, strategy selection, try-out, and revision also nest on the assumption that behavior is predictable. The procedural counterpart of behavioral instructional theory is therefore analytical and empirical, that is, reductionist. If behavior is predictable, then the designer can select the most effective instructional stimuli simply by following the procedures described in an instructional design model. Instructional failure is ascribed to the lack of sufficient information, which can be corrected by doing more analysis and formative testing.

5.5.3 Cognitive Theory and the Predictability of Behavior

The main theme of this chapter has been cognitive theory. We have argued that cognitive theory provides a much more complete account of human learning and behavior because it considers factors that mediate between the stimulus and the response, such as mental processes and the internal representations that they create. We have documented the ascendancy of cognitive theory and its replacement of behavioral theory as the dominant paradigm in educational psychology and technology. However, the change from behavioral to cognitive theories of learning and instruction has not been accompanied by a parallel change in the procedures of instructional design through which the theory is implemented.

You might well ask why a change in theory should be accompanied by a change in procedures for its application. The reason is that cognitive theory has essentially invalidated the basic assumption of behavioral theory, that behavior is predictable. Since the same assumption underlies the analytical, empirical, and reductionist technology of instructional design, the validity of instructional design procedures is inevitably called into question.

Cognitive theory's challenges to the predictability of behavior are numerous and have been described in detail elsewhere (Winn, 1987, 1990, 1993). The main points may be summarized as follows:

1. Instructional theory is incomplete. This point is trivial at first glance. However, it reminds us that there is not a prescription for every possible combination of instructional conditions, methods, and outcomes. In fact, instructional designers frequently have to select strategies without guidance from instructional theory. This means that there are often times when there are no prescriptions with which to predict student behavior.

2. Mediating cognitive variables differ in their nature and effect from individual to individual. There is a good chance that everyone s response to the same stimulus will be different because everyone's experiences, in relation to which the stimulus will be processed, are different. The role of individual differences in learning and their relevance to the selection of instructional strategies has been a prominent theme in cognitive theory for 2 decades (Cronbach & Snow, 1977; Snow, 1992). Individual differences make it extremely difficult to predict learning outcomes for two reasons. First, to choose effective strategies for students, it would be necessary to know far more about the student than is easily discovered. The designer would need to know the student's aptitude for learning the given knowledge or skills, the student's prior knowledge, motivation, beliefs about the likelihood of success, learning style, level of anxiety, and stage of intellectual development. Such a prospect would prove daunting even to the most committed determinist! Second, for prescriptive theory, it would be necessary to construct an instructional prescription for every possible permutation of, say, high, low, and average levels on every factor that determines an individual difference. This obviously would render instructional theory too complex to be useful for the designer. In both the case of the individual student and of theory, the interactions among many factors make it impossible in practice to predict what the outcomes of instruction will be. One way around this problem has been to let students decide strategies for themselves. Learner control (Merrill, 1988; Tennyson & Park, 1987) is a feature of many effective computer-based instructional programs (see 33.1). However, this does not attenuate the damage to the assumption of predictability. If learners choose their course through a program, it is not possible to predict the outcome.

3. Some students know how they learn best and will not necessarily use the strategy the designer selected for them. Metacognition is another important theme in cognitive theory. It is generally considered to consist of two complementary processes (Brown, Campione & Day, 1981). The first is students' ability to monitor their own progress as they learn. The second is to change strategies if they realize they are not doing well. If students do not use the strategies that instructional theory suggests are optimal for them, then it becomes impossible to predict what their behavior will be. Instructional designers are now proposing that we develop ways to take instructional metacognition into account as we do instructional design (Lowyck & Elen, 1994).

4. People do not think rationally as instructional designers would like them to. Many years ago, Collins (1978) observed that people reason "plausibly." By this he meant that they make decisions and take actions on the basis of incomplete information, hunches, and intuition. Hunt

(1982) has gone so far as to claim that plausible reasoning is necessary for the evolution of thinking in our species. If we were creatures who made decisions only when all the information needed for a logical choice was available, we would never make any decisions at all and would not have developed the degree of intelligence that we have! Schon's (1983, 1987) study of decision making in the professions comes to a conclusion that is similar to Collins's. More recently, research in situated learning (Brown, Collins & Duguid, 1989; Lave & Wenger, 1991; Suchman, 1987) has demonstrated that most everyday cognition is not "planful" and is most likely to depend on what is afforded by the particular situation in which it takes place. The situated nature of cognition has led Streibel (1991) to claim that standard cognitive theory can never act as the foundational theory for instructional design. Be that as it may, if people do not reason logically, and if the way they reason depends on specific and usually unknowable contexts, their behavior is certainly unpredictable.

These and other arguments (see Csiko, 1989) are successful in their challenge to the assumption that behavior is predictable. The bulk of this chapter has described the factors that come between a stimulus and a student's response that make the latter unpredictable. Scholars working in our field have for the most part shifted to a cognitive orientation when it comes to theory. However, they have not shifted to a new position on the procedures of instructional design. Since these procedures are based, like behavioral theory, on the assumption that behavior is predictable, and since the assumption is no longer valid, the procedures whereby educational technologists apply their theory to practical problems are without foundation.

5.5.4 Cognitive Theory and Educational Technology

The evidence that educational technologists have accepted cognitive theory is prominent in the literature of our field (Gagné & Glaser, 1987; Richey, 1986; Spencer, 1988; Winn, 1989a). Of particular relevance to this discussion are those who have directly addressed the implications of cognitive theory for instructional design (Bonner, 1988; Champagne, Klopfer & Gunstone, 1982; DiVesta & Rieber, 1987; Schott, 1992; Tennyson & Rasch, 1988). Collectively, scholars in our field have described cognitive equivalents for all stages in instructional design procedures. Here are some examples.

Twenty years ago, Resnick (1976) described "cognitive task analysis" for mathematics. Unlike behavioral task analysis, which produces task hierarchies or sequences (Gagné, Briggs & Wager, 1988), cognitive analysis produces either descriptions of knowledge schemata that students are expected to construct, or descriptions of the steps information must go through as the student processes it, or both. Greeno's (1976, 1980) analysis of mathematical tasks illustrates the knowledge representation approach and corresponds in large part to instructional designers' use of information mapping that we discussed in section 5.3. Resnick's (1976) analysis of the way children perform subtraction exemplifies the information-processing approach.

Cognitive task analysis gives rise to cognitive objectives, counterparts to behavioral objectives. In Greeno's (1976) case, these appear as diagrammatic representations of schemata, not written statements of what students are expected to be able to do, to what criterion, and under what conditions (Mager, 1962).

The cognitive approach to learner analysis aims to provide descriptions of students' mental models (Bonner, 1988), not descriptions of their levels of performance prior to instruction. Indeed, the whole idea of "student model" that is so important in intelligent computer-based tutoring (Van Lehn, 1988) very often revolves around ways of capturing the ways students represent information in memory and how that information changes, not on their ability to perform tasks.

With an emphasis on knowledge schemata and the premise that learning takes place as schemata change, cognitively oriented instructional strategies are selected on the basis of their likely ability to modify schemata rather than to shape behavior. If schemata change, DiVesta and Rieber (1987) claim, students can come truly to understand what they are learning, not simply modify their behavior.

These examples show that educational technologists concerned with the application of theory to instruction have carefully thought through the implications of the shift to cognitive theory for instructional design. Yet in almost all instances, no one has questioned the procedures that we follow. We do cognitive task analysis, describe students' schemata and mental models, write cognitive objectives, and prescribe cognitive instructional strategies. But the fact that we do task and learner analysis, write objectives, and prescribe strategies has not changed. The performance of these procedures still assumes that behavior is predictable, a cognitive approach to instructional theory notwithstanding. Clearly something is amiss.

5.5.5 Can Instructional Design Remain an Independent Activity?

We are at the point where our acceptance of the assumptions of cognitive theory forces us to rethink the procedures we use to apply it through instructional design. The key to what is necessary lies in a second assumption that follows from the assumption of the predictability of behavior. That assumption is that the design of instruction is an activity that can proceed independent of the implementation of instruction. If behavior is predictable and if instructional theory contains valid prescriptions, then it should be possible to perform analysis, select strategies, try them out, and revise them until a predetermined standard is reached, and then deliver the instructional package to those who will use it, with the safe expectation that it will work as intended. If, as we have demonstrated, that assumption is not tenable, we must also question the independence of design from the implementation of instruction (Winn, 1990).

There are a number of indications that educational technologists are thinking along these lines. All conform loosely with the idea that decision making about learning strategies must occur during instruction rather than ahead of time. In their details, these points of view range from the philosophical argument that thought and action cannot be separated, and therefore the conceptualization and doing of instruction must occur simultaneously (Nunan, 1983; Schon, 1987), to more practical considerations of how to construct learning environments that are adaptive, in real time, to student actions (Merrill, 1992). Another way of looking at this is to argue that, if learning is indeed situated in a context (for arguments on this issue, see McLellan, 1996), then instructional design must be situated in that context, too.

A key concept in this approach is the difference between learning environments and instructional programs. Other chapters in this volume address the matter of media research. Suffice it to say here that the most significant development in our field that occurred between Clark's (1983) argument that media do not make a difference to what and how students learn and Kozma's (1991) revision of this argument was the development of software that could create rich multimedia environments. Kozma (1994) makes the point that interactive and adaptive environments can be used by students to help them think, an idea that has a loot in common with Salomon's (1979) notion of media as "tools for thought." The kind of instructional program that drew much of Clank's (1985) disapproval was didactic— designed to do what teachers do when they teach towards a predefined goal. What interactive multimedia systems do is allow students a great deal of freedom to learn in their own way rather than in the way the designer prescribes. Zucchermaglio (1993) refers to them as "empty technologies" that, like shells, can be filled with anything the student on teacher wishes. By contrast, "full technologies" comprise programs whose content and strategy are predetermined, as is the case with computer-based instruction (see 12.2.3).

We believe that the implementation of cognitive principles in the procedures of educational technology requires a reintegration of the design and execution of instruction. This is best achieved when we develop stimulating learning environments whose function is not entirely prescribed but which can adapt in real time to student needs and proclivities. This does not necessarily require that the environments be "intelligent" (although at one time that seemed to be an attractive proposition [Winn, 1987]). It requires, rather, that the system be responsive to the student's intelligence in such a way that the best ways for the student to learn are determined, as it were, "on the fly."

5.5.6 The Three "Ages" of Scholarship in Educational Technology

We summarize the main points in this section by describing the three ages of educational technology. We call these the *age of instructional design,* the *age of message design,* and the *age of environment design.*

The age of instructional design is dominated by behavioral theories of learning and instruction and by procedures for applying theory to practice that are based ultimately on the assumption that behavior is predictable. The decisions instructional designers make are driven almost exclusively by the nature of the content students are to master. Thus, task analysis, which directs itself to an analysis of content dominates the sources of information from which strategy selection is made. The most important criterion for the success of the techniques used during the age of instructional design is whether on not they produce instruction that is as successful as a teacher. Clank's (1983) criticism of research in our field is leveled at instructional systems that attempt to meet this criterion.

In the age of message design, the emphasis shifts from instructional content to instructional formats. We believe that this is the immediate result of the concern among cognitive theorists with the way information is represented in memory, schemata, and mental models. There is an assumption (doubtless incorrect; see Salomon, 1979) that the format selected to present information to students in some way determines the way in which the information is encoded in memory. A less-restrictive form of this assumption has, however, produced a great deal of useful research about the relationship between message forms and cognition. Fleming and Levie (1993) provide an excellent summary of this work.

The age of environment design is likewise based on cognitive theory. However, its emphasis is on providing information from which students can construct understanding for themselves through interaction that is more or less constrained, depending on students' needs and wishes. The key to success in this third, current, age is in the interaction between student and environment rather than in content or information format. A good example of this orientation in instructional design is Merrill's (1992) transaction theory, where the instructional designer's main focus in prescribing instruction is the kind of transaction (interaction) that occurs between the student and the instructional program. Another example is the design of learning environments based in the technologies of virtual reality (Winn, 1993). In virtual environments, the interaction with the environment is potentially so intuitive as to be entirely transparent to the user (Bricken, 1991). However, just what the participant in a virtual environment is empowered to do and particularly the way in which the environment reacts to participant actions (Winn & Bricken, 1992) requires the utmost care and attention from the instructional designer.

5.5.7 Section Summary

In this section we have reviewed a number of important issues concerning the importance of cognitive theory to what educational technologists actually do, namely, design instruction. This has led us to consider the relations between theory and the procedures employed to apply it in practical ways. We observed that when behaviorism was the dominant paradigm in our field, both the theory and the procedures for its application adhered to the same basic assumption, namely, that human behavior is predictable. We then noted that our field was effective in subscribing to the tenets of cognitive theory, but that the procedures for applying that theory remained unchanged and continued to subscribe to the by-now discredited assumption that behavior is predictable. We concluded by suggesting that cognitive theory requires of our design procedures that we create learning environments in which learning strategies are not entirely predetermined, which requires that the environments be highly adaptive to student actions. Recent technologies that permit the development of virtual environments offer the best possibility for realizing this kind of learning environment.

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