Learning Processes and Learning Outcomes

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Learning, the acquisition of new knowledge and skills, is generally regarded as a constructive activity. The construction, however, can assume many forms. Individuals differ in *how* they learn (processes) as well as *what* they learn (outcomes). Bower and Hilgard (1975 p. 1) have summarized this relationship: "as a process is to its result, as acquiring is to a possession, as painting is to a picture." Yet painters differ: they have diverse experiences, use different techniques, and thus produce quite different pictures. The same is true of learners; different outcomes of learning (e.g., propositional knowledge, procedural skills) reflect differences in learning processes (e.g., encoding skills, attention allocation). This entry examines the roots of our understanding of learning processes and outcomes, surveys the state of knowledge, and depicts a model of learning based on this information.

1. Historical Background

Philosophers and psychologists have debated the issue of how humans learn for centuries. This controversy can be reduced to two perspectives: empiricism (i.e., experience is the sole source of learning) and rationalism (i.e., reasoning is the basis of learning). While both positions agree that learning is basically constructive in nature, explanations differ greatly as to how the construction occurs.

1.1 Empiricism

Empiricism posits that learning results from sensory experiences in the world. Complex conceptions can be reduced to simple ideas, which arise from the association of contiguous experiences. Associative "bonds" connect simple ideas, and the bonds can reflect temporal or causal relations. Furthermore, bonds may be strengthened or weakened as a result of additional experiences. The strength of a bond is dependent on the intensity and meaningfulness of the experience, as well as its frequency, duration, and recency of occurrence.

In addition to association-building, empiricists propose a second fundamental learning process, reflection. This relates to the collection and comparison of several ideas at once. With reflection, it is possible to abstract general information from related concepts, enabling inferences and deductions to be made about events and ideas. The philosophy of empiricism (supported by Hobbes, Locke, Hume, and Mill), spawned psychological research on associative learning and behaviorism.

Associative learning processes were first objectively measured in the laboratory established by Wilhelm Wundt in 1879 at the University of Leipzig in Germany. The German psychologist Hermann Ebbinghaus also investigated associative learning phenomena, and is credited with starting the verbal learning tradition in 1885 when *Uber das Gedächtnis* (Memory) was first published (Ebbinghaus 1913). Ebbinghaus additionally demonstrated that statistical analyses could be used to make assertions about the significance of different learning variables. E L Thorndike's landmark research on connectionism in the late nineteenth and early twentieth century further advanced associative-learning research and laid the foundation for the behaviorists.

During the first half of the twentieth century psychological research in the United States was dominated by "behaviorism," initiated by John Watson. The behaviorists argued that psychological research should focus on specific stimuli and observable responses. This movement was influenced by the work of Ivan Pavlov in Russia before the First World War, then by B F Skinner, in the United States (starting in the 1930s). Building on the findings of both Pavlov and Thorndike, Skinner proceeded to study more complex forms of behavior. In general, behaviorism asserted that learning outcomes (i.e., observable behaviors) were solely accounted for by the processes of forming associations and reflection. Thus, they saw no need to postulate intervening, cognitive operations.

1.2 Rationalism

Rationalism disagrees with the basic premise of empiricism that all knowledge is reducible to elementary inputs and associations. Rationalist philosophers (e.g., Descartes, Leibniz, and Kant) held that incoming sensory data merely provided the raw material for use by "interpretive mechanisms," postulated to be part of our innate endowment. These mechanisms serve to impose structure or constraints on learning.

Rationalists cited a wide range of mental phenomena that could not be accounted for by empiricism. For instance, empiricism offered no provision for the organization of information. Also, the solution of novel problems (e.g., "insight" problems) could not be adequately explained by simply applying existing knowledge to new situations. Other phenomena, such as language acquisition, infants' perception of depth, and a predisposition to ascribe "causality" to events, imply some innate or emergent property that goes beyond the reductionist view underlying empiricism. Rationalism inspired Gestalt psychology.

During the early twentieth century when behaviorism was gaining momentum in the United States, Gestalt psychology was being developed by three German psychologists: Max Wertheimer, Kurt Koffka, and Wolfgang Köhler. They disagreed with behaviorists on the issue that psychology should be limited to observable behavior. Rather, they believed that learning involved "emergent" properties not derivable from additive combinations of the properties of its elements. Through carefully designed laboratory experiments (e.g., the solution of problems in which there was no prior experience to draw on), they were able to show that learning required an analysis of the entire situation, not just repeating a specific learned response. In general, Gestalt psychology believed that learning was a derivative of innate perceptual and problem-solving processes. Incoming data from the world would be filtered by these processes and then organized into a structure.

1.3 Empiricism and Rationalism

Psychology soon began to integrate theories derived from the empiricist and rationalist traditions. In Britain Frederic Bartlett developed the notion of storing "schemas" (*interpretations* of experiences) rather than exact representations of items or events (Bartlett 1932). Subsequently, Jean Piaget, a Swiss psychologist, worked on the idea that schemas undergo fundamental changes from infancy to adolescence (Piaget 1954). Cognitive psychology arose in the 1950s, employing established approaches in conjunction with newer ideas and techniques to examine mental processes and learning. In particular, cognitive psychology benefited from computers that were beginning to appear at this time. Computers enabled precise measurements to be obtained within controlled learning environments and provided the basis for the metaphor of the human mind as an information-processing device. During the 1970s and 1980s cognitive research focused on the analysis of expertise, mostly in the areas of memory, problem-solving, and language.

1.4 Instructional Psychology

Starting in the 1980s, instructional psychology became an important and separate part of mainstream cognitive psychology. This new research stream highlighted the issue of transitioning novices to experts, which gained increased attention with the advent of intelligent computer-assisted instruction (Mandl and Lesgold 1988). The critical question within this field is: what characteristics of the learner should be assessed in order to contribute to a science of instruction?

According to prominent researchers in the field (e.g., Glaser and Bassok 1989, Snow 1990), there are three main elements to a theory of instruction: (a) analysis of the initial state of knowledge and skill; (b) description of the desired or end state of knowledge and skill (learning outcome); and (c) explanation of the learning processes that serve to take a learner from the initial state to the desired state accomplished in instructional settings.

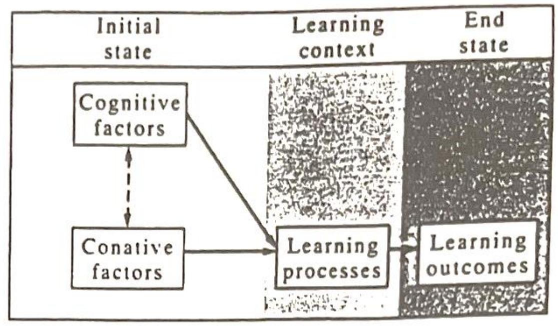

Figure 1
Simple Model of learning

2. Theoretical Framework of Learning

A simple theoretical framework to guide research in this field is shown in Fig. 1. The initial state of the learner influences learning processes (within some learning context or "environment") and these processes affect learning outcome. The influence of learning contexts may be direct or may interact with characteristics of the learner to affect the learning outcome. The main components of learning will now be discussed.

2.1 Initial States

Two basic determinants of learning and performance are cognitive and conative aptitudes. Cognitive aptitudes refer to mental processes and structures associated with knowledge and skill acquisition, such as working-memory capacity and general knowledge (Anderson 1983). Conative aptitudes refer to mental conditions or behaviors directed toward some event (Kanfer 1989). One main difference between these two factors is that the conative aptitudes, in general, are more malleable than the cognitive aptitudes, which tend to represent more stable abilities (Baron 1985). Figure 2 represents an elementary depiction of the initial states with arrows implying possible direction of influence.

2.1.1 Cognitive factors. Learning depends on a person's prior knowledge and cognitive skills. These

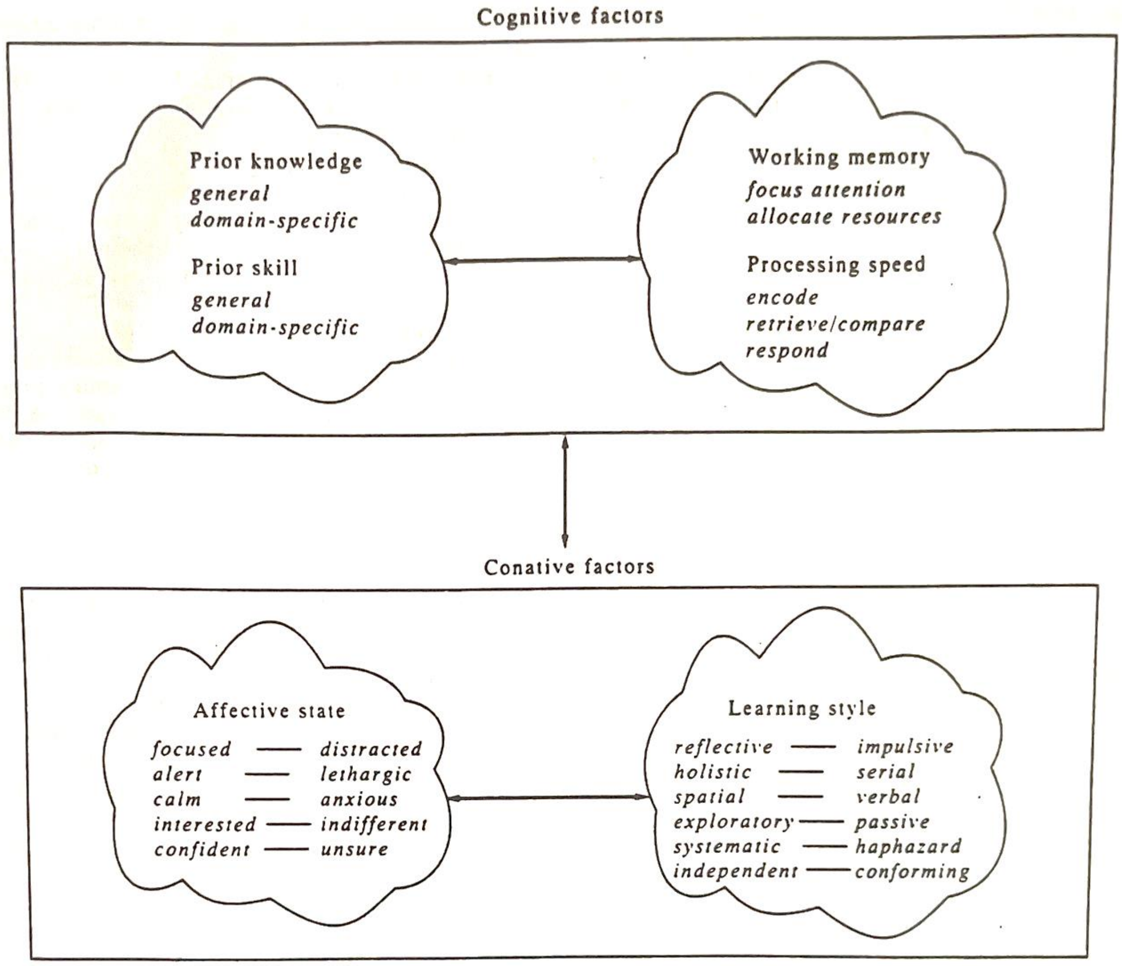

Figure 2
Initial States of the learner

mental characteristics comprise the cognitive factors that govern knowledge and skill acquisition. Kyllonen and Christal (1989) have differentiated these cognitive factors into two main categories: "enablers" and "mediators" of learning.

Enablers consist of what a person already knows and can transfer to new situations (i.e., the depth, breadth, accessibility, and organization of knowledge possessed by a learner). In fact, some researchers have argued that an individual's knowledge structure is the primary determinant of new learning (e.g., Chi et al. 1982, Dochy 1992).

The degree to which an individual's knowledge structure is organized influences both the speed and accuracy by which new knowledge and skills are acquired and retrieved. Glaser and Bassok (1989 p. 26) argued that "structured knowledge enables inference capabilities, assists in the elaboration of new information, and enhances retrieval. It provides potential links between stored knowledge and incoming information, which facilitate learning and problem solving."

Mediators represent limits on the maintenance, storage, and retrieval of information, thus governing the quality and rate of knowledge and skill acquisition. Examples of mediators include working-memory capacity and information-processing speed.

Working memory, in general, is defined as the temporary storage, or activation level, of information being processed (Baddeley 1986). Two processes associated with this measure are (a) focusing attention, and (b) allocating cognitive resources. Working-memory capacity has repeatedly been shown to be a strong predictor of learning across many and varied learning tasks (Anderson 1987, Kyllonen and Christal 1990).

Information-processing speed refers to the rate at which learners acquire and apply new knowledge or skills. The affiliated processes for this cognitive measure include: encoding, storing, retrieving, comparing, and responding to information. While these processes tend to be independent, they are relatively stable across content areas. That is, fast encoders may be slow retrievers, but fast encoders on a word task tend to be fast encoders on a numeric task (Kyllonen and Christal 1989). While enablers are consonant with empirical learning, mediators tend to reflect the rationalist view of innate mechanisms.

2.1.2 Conative factors. In order to learn, individuals need to focus their attention and persist in a new learning task, despite difficulties they may encounter. Individual differences in these behaviors reflect affective as well as learning style differences. These two categories are clustered together under the heading of "conative factors" representing separate but correlated learner attributes.

Affective state, generally, describes an individual's feelings, attitudes, and emotions. Affective states may be altered by external conditions (e.g., a pending exam affecting anxiety) or internal conditions (e.g., sleep deprivation affecting arousal). The affective state of the learner can have a profound influence on learning or performance. For example, Yerkes and Dodson (1908) found a relationship between arousal/anxiety and performance. Foot shocks were administered to subjects while they were learning a visual discrimination task, which ranged from easy to difficult. When the task was easy, increasing the shock level (and thus the anxiety level) actually increased performance on the task. But when the task became more difficult, a negative relation was found between shock level and performance. Optimal performance was associated with moderate levels of foot shocks.

Another set of studies examined the relationship between arousal and learning processes during performance on various learning tasks (Revelle 1989). A memory-search task was used and an individual's affective state (arousal) was manipulated by the administration of caffeine. Learning processes were shown to be differentially affected by arousal. Some processes were facilitated by caffeine intake (e.g., reduced reaction times to respond to items) while other were impaired (e.g., increased latencies associated with processing items in short-term memory, such as encoding and comparing stimuli).

Learning styles refer to "general behavioral dispositions that characterize performance in mental tasks" (Baron 1985 p.366). They can be viewed as parameters of thinking (under voluntary control) with optimum levels for a particular situation. For instance, being "reflective" is often a positive mental trait, but in some cases (e.g., a vigilance task requiring rapid responses), persisting in this style can be detrimental to performance. Whereas affective states are manipulable and transitory, learning styles are comparatively more stable. However, style does imply a preferred orientation toward learning, so it should also be manipulable through instruction or other situational influences.

Probably the most researched learning style measure is reflectivity–impulsivity, the tendency to be accurate at the expense of speed in learning or problem-solving situations. Slower, more accurate processing is equated with a reflective style, while faster, less accurate processing is associated with an impulsive style. Messer (1976) found a negative correlation between impulsivity and IQ: when IQ was held constant, an inverse relationship still held between impulsivity and school performance. Impulsive individuals may not allocate sufficient time for processing information during the learning process, thereby negatively impacting learning outcome. Thus, learning styles may be associated with different learning processes, and learning processes differentially affect learning outcome.

2.2 Learning Processes

The operational definition of learning used in this entry is that learning is a process of constructing relations. These relations can become progressively more complex with increased experience. Learning processes may therefore be defined as any series of mental actions directly responsible for this construction (or learning outcome). This broad definition encompasses a wide range of mental actions, differing in nature as well as in scope of application. To organize the many and varied processes cited in the literature, a framework will be employed, consisting of four learning-type categories, each with its own constituent processes. Three categories are arrayed along a dimension of increasing complexity, from basic associative learning processes (constructing simple relations), followed by procedural learning processes (constructing relations among simple relations) and ending with the more complex processes involved with inductive reasoning (organizing relations into a coherent structure). Furthermore, these three categories of learning are believed to be influenced, or controlled, by a fourth category: metacognition. Figure 3 shows the organization of the learning processes as presented in this entry.

2.2.1 Associative learning. As was discussed in the historical review section, the idea that associative learning processes are important to knowledge and skill acquisition has been held for a long time. Furthermore, contemporary studies continue to offer ample support for this proposition (e.g., Kyllonen and Tirre 1988). The processes affiliated with associative learning are believed to represent fundamental learning abilities, involving the rate and quality of forming associations or links between new and old knowledge. These processes include: encoding and storing information from the environment and retrieving information from memory.

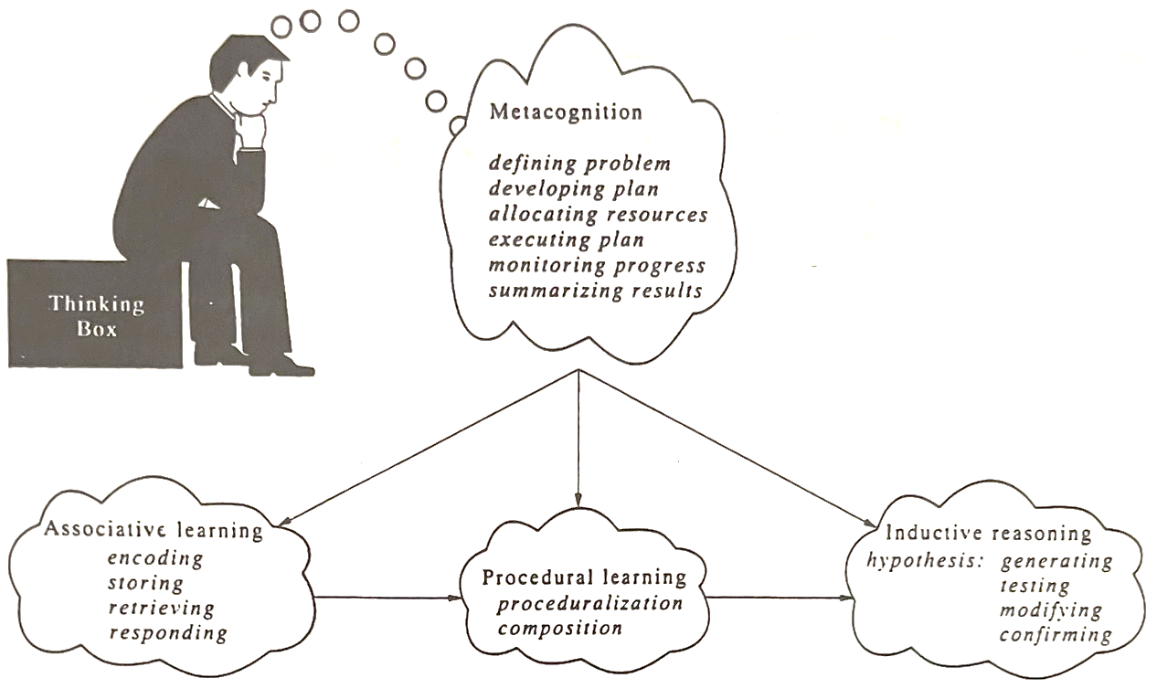

Figure 3
Learning processes

An individual's existing knowledge base greatly affects the construction of new associations. Broader knowledge bases make it easier to establish new associations and also contribute to more distinctive and memorable associations being formed. Consider the following facts: (a) the atomic number of Nitrogen is 7, (b) force = mass × acceleration; and (c) two angles whose sum is 90 degrees are "complementary angles." Learning these items in isolation, without related knowledge, is difficult, requiring studied rehearsing or elaborative processing. However, if some related knowledge existed, new knowledge could be attached to it. For instance, knowing other geometry principles would aid the acquisition of the new fact concerning complementary angles.

Thus, basic associative learning processes facilitate the formation of relationships between novel and existing knowledge; they constitute the mortar for the building blocks of knowledge. The quantity and quality of associated knowledge influence learning outcome as well as the rate at which these developing associations may be stored and accessed. In short, an individual's ability to encode, store, and retrieve information reflects the efficacy of the associative learning processes. These processes are directly influenced by the cognitive and conative factors discussed earlier. For instance, the speed and accuracy of encoding a new unit of information are constrained by an individual's processing speed and working-memory capacity.

2.2.2 Procedural learning. While associative learning processes serve to establish simple relations between facts or concepts, procedural learning processes go a step further to establish relations between relations or "rules." Any unit of knowledge may be represented in the form of "if–then" rules (also known as procedures). Procedures may be general (e.g., how to work backward from a goal) or specific (e.g., how to measure the diameter of a circle). Furthermore, procedural learning can be characterized by the processes related to compiling rules into efficient skills. This is called "knowledge compilation" in the psychological literature.

According to Anderson (1987), knowledge compilation consists of two related processes: proceduralization and composition. Proceduralization is the process that takes a general rule and modifies it into one specialized for a particular task. The general procedure thus serves as a template for the formation of a more domain-specific production or rule. For example, the general rule of working backward from a goal could be applied to a computer programming problem. Given a particular programming problem (or goal state), a programmer could decompose the larger problem into subgoals and attempt to solve each in turn. This general rule could be applied across various domains (e.g., electronics troubleshooting, medical diagnosis) or within a domain (e.g., within a computer programming problem, knowing the procedure for

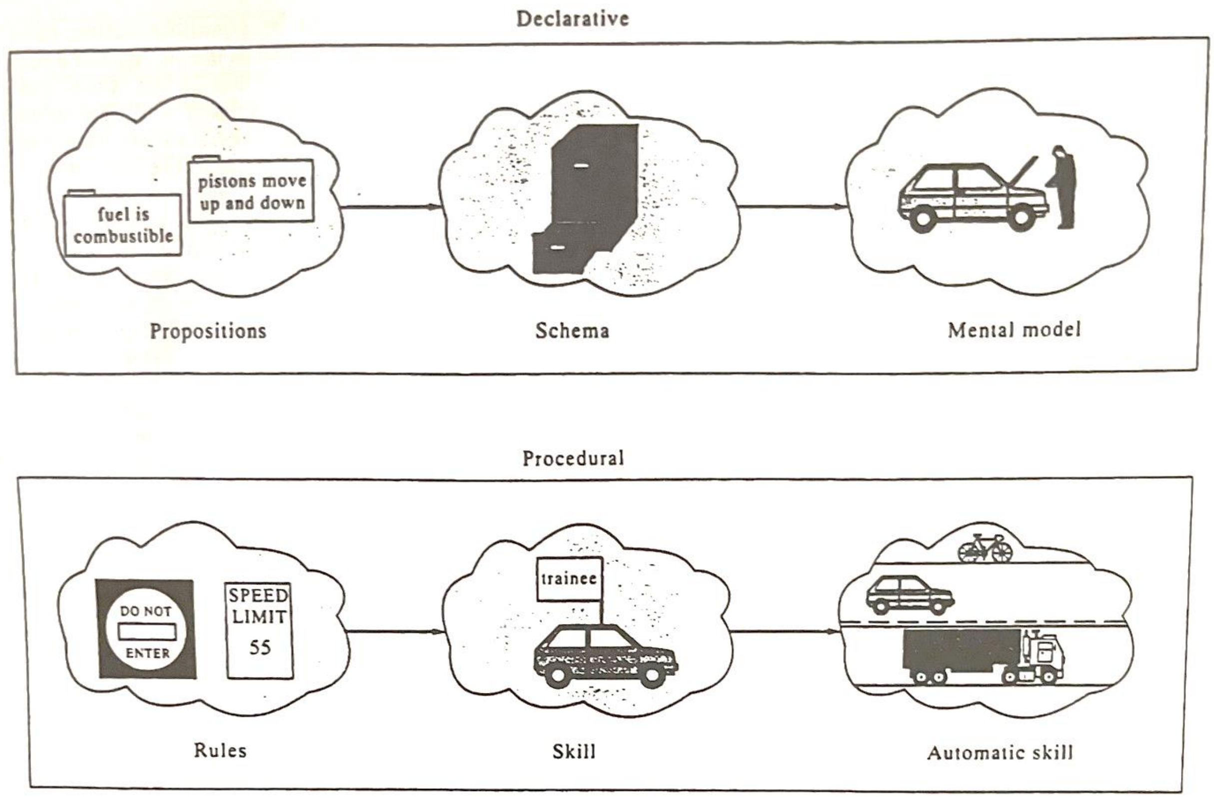

Figure 5
Learning outcomes

performance supported their perceptions. In contrast, when younger children indicated they had memorized the items, their actual recall performance was faulty. Younger children could specify the goal of the task, but were mostly unsuccessful in applying the other metacognitive processes and thus unsuccessful in their outcome performance.

In summary, four types of learning with their associated processes have been postulated to influence learning outcome: associative learning, procedural learning, inductive reasoning, and metacognition. Individual differences in the application of these processes constitute a major determinant of learning outcome and will be discussed below.

2.3 Learning Outcomes

The outcome of learning refers to any change within an individual's knowledge structure that results from a learning situation. Outcomes of learning can be quite diverse, differing in magnitude (e.g., learning a simple fact versus a complex technical skill) as well as content area (e.g., affective and social skills, motor skills, procedural knowledge).

One way of characterizing the wide assortment of learning outcomes can be seen in Fig. 5. The distinction between declarative and procedural outcomes is fundamental but refinements are possible within each of these two categories: declarative knowledge and procedural skills can both be arrayed by complexity.

2.3.1 Declarative knowledge outcomes. The basic unit of information underlying declarative knowledge outcomes is the proposition. It is represented by a single, isolated postulate (e.g., gasoline is a volatile mixture of liquid hydrocarbons). A collection of related postulates comprises a concept—any general, abstract idea constructed from experiences in the world (e.g., gasoline: is a fuel for automobiles, derived from crude petroleum; is used in liquid form; has a distinctive odor; is highly combustible, etc.). Infants begin learning concepts from sensory inputs (i.e., associative bonding and rudimentary reflection). Later, more abstract concepts are formed, such as the notion of the permanence of objects and invariant properties of numbers. Concepts are stored in memory along with their defining characteristics. They are always subject to revision and extension as a result of new experiences in the world.

The next level of declarative knowledge outcome is the schema, defined as an interconnected set of propositions and concepts representing a situation. Schemas form the basis for comparing and interpreting incoming data. They also shape individuals' expectations and hence what is perceived. Yet schemas, based on prior knowledge and beliefs, can lead to erroneous inferences if the foundation is deficient or contains misconceptions. For instance, John's prior experiences were limited to full-service gas stations, then the first time he drove into a self-service gas station, his "gas station schema" would dictate a wait in the car until the attendant arrived. Observing other drivers filling up their gas tanks may prompt him to follow suit. In that case, John would have learned some important new information causing the modification of the existing schema.

The most organized declarative knowledge structure is the mental model, a highly organized set of propositions, concepts, and rules for relating them to one another. Together, these represent an integrated system (e.g., electrical circuit, human respiratory system). A mental model is structured hierarchically; different levels of analysis are possible. At each level of analysis, one can know: information about component parts, how they are connected, and how the system functions as a whole. As an example, the following is a mental model (mid- to high-level) of how mechanical energy is used to drive a car. Fuel lines feed gasoline to the area of the spark plugs. Spark plugs receive energy from the distributor (or electronic ignition) causing a spark to occur. The spark ignites the fuel causing it to explode in a controlled manner. The explosion drives the piston down, and the descending piston drives another piston up and also creates a vacuum causing more fuel to enter the area. Pistons going up and down rotate the crankshaft and this mechanical energy is used to drive the car. In this example, more detailed levels of analysis are possible. This mental model can also be extended for use in understanding other mechanical systems with similar components (e.g., motorcycle engine, lawn mower, outboard motor).

In summary, declarative knowledge outcomes are arrayed from simple to complex (propositions, schemas, mental models). Furthermore, newly acquired declarative knowledge outcomes can be stored in the long-term memory for use in subsequent acquisition of declarative knowledge or procedural skills, constituting a feedback loop. The learning processes responsible for declarative knowledge outcomes are mostly associative, with some inductive reasoning required for the acquisition of complex schemas and mental models.

2.3.2 Procedural skill outcomes. While declarative learning outcomes relate to knowledge *about* something, procedural learning outcomes relate to knowledge of *how to do* something. A rule is the basic unit of action underlying procedural skill outcomes. Rules are typically represented by condition–action pairs. The condition may be defined as the "if" part of a rule, while the action may be defined as the "then" part, consisting of the associated steps of some procedure. If, for example, you want to bake a potato, then place the potato in the microwave oven and set the timer for 6 minutes.

The next level of procedural outcome is a skill, defined as a collection of related rules. A skill may be cognitive (e.g., computing the square root of a number), motor (e.g., typing), social (e.g., using the proper fork at a formal dinner), or even creative (e.g., composing a poem). For example, if you wanted to add two two-digit numbers, such as 49 + 33, then first add digits in the "ones" column (9 + 3 = 12). If the sum exceeds 10, then write what remains under the "ones" column (2) and carry a 1 to the "tens" column. Next, add all digits in the "tens" column (1 + 4 + 3 = 8). The final sum is 82.

Finally, a skill may become automatic after considerable practice applying that skill in many and varied situations. Eventually an automatic skill requires little or no conscious effort. For instance, after years of practice driving a car (involving a complex coordination of skills), a person can drive the car in traffic while listening to the radio and planning the evening meal. The execution of this procedure is almost unconscious, compared to the step-by-step manner of invoking procedures, outlined above.

In summary, learning outcomes may be declarative or procedural in nature, and may further be distinguished by level of complexity. Moreover, the learning processes are believed to affect outcomes differentially. Associative learning processes directly affect declarative knowledge outcomes (but can also affect simple rule-learning), procedural learning processes primarily affect skill acquisition. Inductive reasoning processes affect both declarative and procedural outcomes. Metacognitive processes influence learning outcome indirectly, through the other learning processes.

3. A Model of Learning

The purpose of this entry was to examine possible relations among initial states, learning processes, and learning outcomes in order to devise a model of learning. To benefit instructional psychology, a model of learning requires empirically derived information concerning which of the initial states and learning processes affect which outcome measures, how they exert their influence, and what instructional techniques may be used to enhance the processes (and hence the outcome). In addition, each outcome measure requires detailed information about how to test for the presence and quality of various knowledge types. Over time, sufficiently detailed information could be assembled

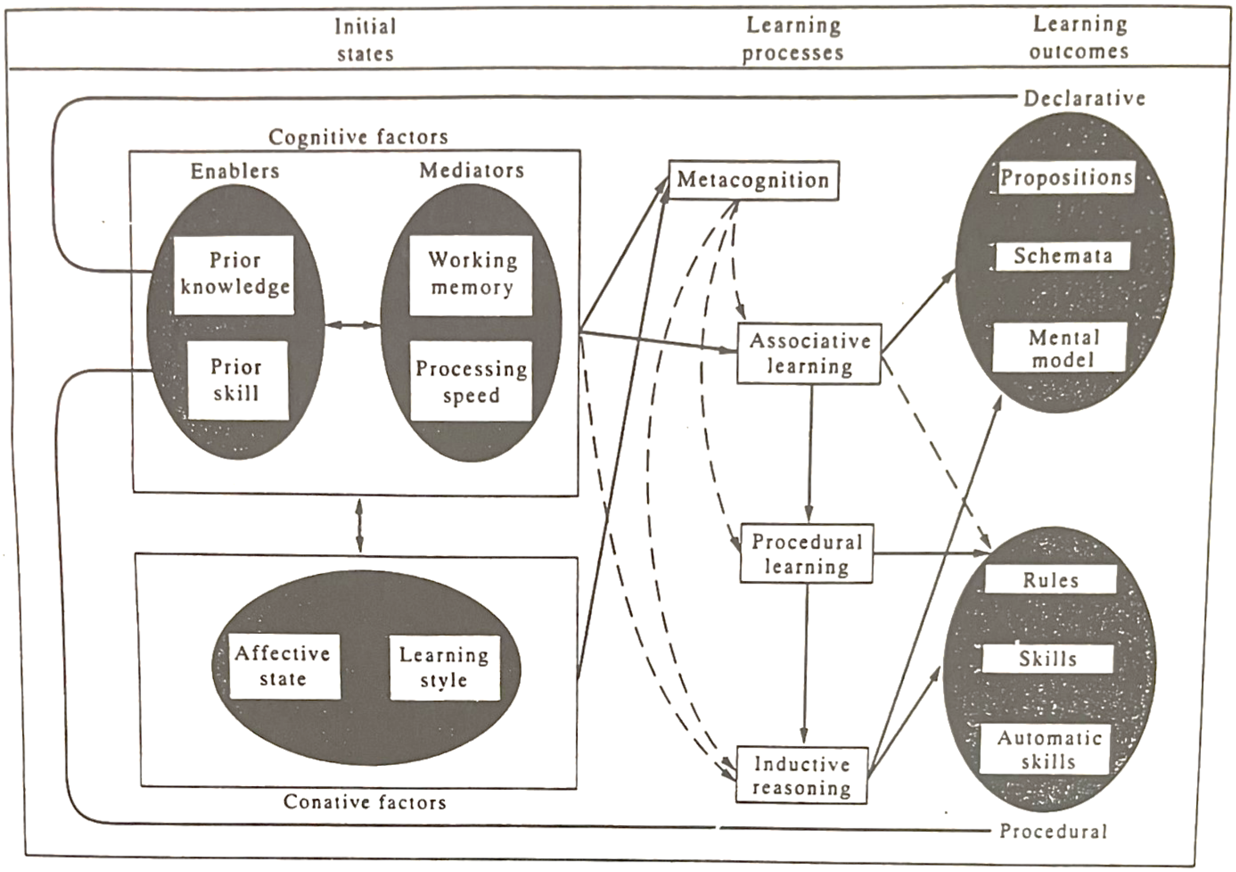

Figure 6
Model of learning

to guide the development of principled instruction across a wide range of curriculum goals.

An attempt at outlining such a model appears in Fig. 6, integrating the components discussed in this entry and representing an expansion of the simple model depicted in Fig. 1. Arrows in the figure represent both real and hypothetical relationships among initial states, learning processes, and learning outcomes. Solid lines denote direct relations and dashed lines represent less direct relations.

This model shows the two initial states (cognitive and conative factors) influencing the learning processes. In particular, the cognitive factors directly impact metacognition, associative learning, procedural learning, and inductive reasoning. These relations have been documented in the literature. The conative factors, however, are depicted as only impacting metacognition, but other relationships are possible (e.g., reflective learning style may facilitate associative learning processes, which enhance declarative knowledge outcomes).

Metacognitive processes monitor the efficacy of the three learning processes and, if necessary, invoke different processes during the solution of a particular problem. However, the three learning processes (associative, procedural, and inductive) ultimately impact what is learned. An analogy can be made with a conductor and musicians performing during a symphony. The conductor directs the musicians but does not actually play any music. The quality of the conducting affects the musicians and thus the musical outcome.

Associative learning processes influence declarative knowledge outcomes, but another possible (dashed-line) relationship can be made to procedural learning. That is, rule-learning could be accomplished via associative learning processes where, for instance, a rule could be learned by rote memorization. Next, procedural learning processes influence procedural outcomes. For example, facility in proceduralizing knowledge leads to the development and acquisition of skills. Inductive reasoning processes exert their influence both on declarative outcomes (e.g., formation of mental models) and on procedural outcomes (e.g., induction of rules). Finally, each newly acquired declarative or procedural outcome feeds back to the initial state of the learner.

Additional research is needed on both the direction and strength of the arrows depicted in the proposed model of learning. Another fertile area of research involves examining relationships between instructional environments and learning outcomes. For instance, the acquisition of a mental model may be enhanced by exploratory or discovery environments, while automatizing a perceptual skill may be facilitated in a drill-and-practice environment. In conclusion, the puzzle parts have been presented and an attempt has been made to relate the pieces together.

See also: Architecture of Cognition; Concept Learning; Constructivism and Learning; Declarative and Procedural Knowledge; Feedback in Learning; Learning Activity; Learning Environments; Learning Theories: Historical Overview and Trends; Metacognition; Models of Learning; Self-regulation in Learning

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