Implicit Learning

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Implicit learning is nonepisodic learning of complex information in an incidental manner, without awareness of what has been learned. Implicit learning experiments use 3 different stimulus structures (visual, sequence, and function) and 3 different dependent measures or response modalities (conceptual fluency, efficiency, and prediction and control). Implicit learning may require a certain minimal amount of attention and may depend on attentional and working memory mechanisms. The result of implicit learning is implicit knowledge in the form of abstract (but possibly instantiated) representations rather than verbatim or aggregate representations. Implicit learning shows biases and dissociations in learning different stimulus structures. The dependence of implicit learning on particular brain areas is discussed, some conclusions are drawn for modeling implicit learning, and the interaction of implicit and explicit learning is considered.

Implicit learning as a field of study in cognitive psychology began with A. S. Reber's (1967, 1969) work on artificial grammar learning in the late 1960s. However, interest in implicit learning has exploded in the last decade, beginning with the work of Broadbent and colleagues in dynamic systems research in the early 1980s (Berry & Broadbent, 1984) and continuing with serial reaction time task research (Nissen & Bullemer, 1987) and contingent reaction time task research (Lewicki, Czyzewska, & Hoffman, 1987). The burst of interest in implicit learning (learning complex information without complete verbalizable knowledge of what is learned) comes at least partly as a parallel development to the recent identification and exploration of implicit memory (predominantly, but not solely, unconscious priming effects of previously presented stimuli) in both normal and amnesic patients (Schacter, 1987). It also parallels increased interest in unconscious cognition in general (Baars, 1988; Loftus & Klinger, 1992), including subliminal perception (Merikle, 1992) and disorders of consciousness in brain-damaged populations (McGlynn & Schacter, 1989; A. W. Young & De Haan, 1990). Implicit learning has been proposed as an evolutionary ancestor of explicit thought (A. S. Reber, 1992) and, as such, is considered to have a foundational role in cognition and to be closely related to learning in related animal species (Mishkin, Malamut, & Bachevalier, 1984). Implicit learning may play an important role in the development of procedural knowledge of how complex real-world systems function (Senge & Sterman, 1992). Also, it may be involved in cognitive development (Gelman, 1991) and in social information processing and decision making (Hill, Lewicki, Czyzewska, & Boss, 1989; Nisbett & Wilson, 1977).

Research on implicit learning has generally been concerned with establishing the existence of implicit learning and exploring how implicit and explicit learning may or may not interact. Relatively little research has been performed relating various implicit learning tasks to each other or examining the features and requirements of the implicit learning process itself. The primary goal of this article is to begin to examine these aspects of implicit learning and to identify potential attentional requirements, representational biases, and neural bases.

Implicit learning tasks have used several very different dependent variables (here termed response modalities) to measure learning, as well as several very different stimulus types (visual patterns, sequences, and functions). Theoretically, each response modality can be used with each stimulus type; in practice, however, each stimulus type has tended to be evaluated through a single response modality. This article addresses some basic questions about the implicit learning process. The first set of questions corresponds to the stimulus types and response modalities used in implicit learning. What kinds of stimuli have been used in implicit learning tasks, and how do the stimulus structures used relate to each other? How is implicit learning demonstrated in each response modality, and how is learning in one modality related to learning in others? Are they entirely separate, or can knowledge be transferred from one response modality to another? The second set of questions concerns the attentional requirements of implicit learning. How much attention and early cognitive processing is needed for implicit learning? Can learning occur in nonattended situations? Is implicit learning automatic, or is it affected by different types of cognitive processing of stimuli? Which attentional mechanisms and working memory mechanisms are necessary for implicit learning? A third set of questions explores the representation of implicit knowledge gained through implicit learning. Is it based on verbatim storage of stimuli, aggregate representation of stimulus features, or abstract rules or patterns? If it is based on abstract rules, are the rules linked to surface features of the stimuli? Does the implicit learning process treat all possible stimulus structures equivalently, or is it specialized for or biased?
Definition of Implicit Learning

Before beginning a discussion of the characteristics of implicit learning, it is important to have a set of criteria to provide bounds on the research areas that need to be considered. In the present article, three firm criteria are assumed, as well as an additional guideline that is violated only in unusual cases. The first criterion is that the knowledge gained in implicit learning is not fully accessible to consciousness, in that subjects cannot provide a full (or, in many cases, any) verbal account of what they have learned. Although in all cases subjects do not show (or need not show) verbalizable knowledge of the rules to which they have been exposed, some researchers have used other measures of learning that, they claim, require conscious knowledge. For example, Dulany, Carlson, and Dewey (1984) argued that because subjects could identify which parts of artificial grammar strings made them grammatical or nongrammatical, they had explicit knowledge of the grammar. However, recognition of the grammaticality of partial strings may not reflect knowledge that is any more conscious than recognition of the grammaticality of whole strings.

The second criterion is that subjects learn information that is more complex than a single simple association or frequency count. This criterion was chosen for pragmatic purposes; it allows implicit learning to include only those tasks that involve complex information but avoids prejudging the representation of the information. These first two criteria correspond to that presented by A. S. Reber (1989): Implicit learning is an unconscious learning process that yields abstract knowledge.

The third criterion is that implicit learning does not involve processes of conscious hypothesis testing but is an incidental consequence of the type and amount of cognitive processing performed on the stimuli. This criterion helps to resolve possible controversies about the extent to which subjects are aware of their implicit knowledge: Sometimes subjects have gained some veridical verbalizable knowledge through “just noticing” patterns. However, these subjects have not developed their knowledge through hypothesis-testing methods, and, hence, it can be argued that they have developed it through different mechanisms than those studied in research on hypothesis testing (Bruner, Goodnow, & Austin, 1956; Klayman & Ha, 1987). Subjects may, however, influence implicit learning through other conscious strategies, such as ignoring certain portions of the stimulus (LeCompte, 1992).

In addition to these criteria, as a guideline, implicit learning is preserved in cases of amnesia. Thus, implicit learning must rely on neural mechanisms other than the hippocampal memory system. Because amnesia interferes with the acquisition of episodic memories (memory for autobiographical episodes or events that retain a spatial and temporal context), such preservation is further evidence that implicit learning depends on mechanisms other than those used in inducing explicit knowledge. This guideline is not a firm criterion because there appear to be a few tasks that can be performed by normal subjects in an implicit way but that cannot be either learned or retained by amnesics (e.g., the Hebb digits task; Charness, Milberg, & Alexander, 1988; Milberg, Alexander, Charness, McGlinchey-Berroth, & Barrett, 1988). However, in the other implicit learning tasks, amnesics show normal learning (see Table 7 and the overview of Implicit Learning Tasks section).

The four principles just described are definitional for implicit learning, and the research considered implicit learning here follows them. It should be noted that these criteria each involve very different aspects of the tasks: what is learned (complex information, not simple associations), how it is learned (incidentally, not through hypothesis testing), the status of the information learned (unconscious, not verbalizable), and the neural bases of the learning (nonhippocampal).
Implicit Learning and Related Areas of Cognition

Although implicit learning is similar to the research areas referred to as implicit memory, procedural memory, cognitive skills, and habit learning, there are also important differences. There is also a different meaning of the term *implicit* used by some developmental psychologists. If implicit memory is construed broadly, it includes the field of implicit learning (Schacter, 1987), and, in practice, there is probably no firm dividing line between implicit memory and implicit learning. However, as shown in Table 1, there are differences between most implicit memory studies and implicit learning studies; these differences indicate that implicit learning may profitably be studied as a separate area. Most research in implicit memory consists of priming studies that measure effects of single stimuli, usually words, on performance in a later task, whereas implicit learning involves learning multiple nonverbal stimuli and performing some inductive process on them. The most important difference, then, is that implicit memory involves memory for specific stimuli and implicit learning involves memory for patterns. Another important difference is that the stimuli used in implicit memory are usually words, whereas the stimuli used in implicit learning are nonverbal. There are additional differences as well; for one, in implicit memory research, subjects need not be aware of the connection between the original learning experience and the subsequent test. Schacter (1992) identified five possible conditions of awareness of the earlier task ranging from no awareness (as in anesthesia) to awareness of the task but no awareness of particular items. Schacter concluded that implicit memory can be shown in all five conditions. However, implicit learning may well depend on some degree of memory for the previous learning episode to regain the correct set, as was indicated by Squire and Frambahc’s (1990) inability to show retention of dynamic system control in amnesic patients over a long delay. Another difference is that implicit memory is not influenced by attentional manipulations such as the stimuli being presented with concurrent tasks, being presented as ignored items, and being presented under anesthesia (Moscovitch & Ummita, 1991), whereas implicit learning is affected by these manipulations (these effects are discussed in more detail in the section on attentional requirements).

Despite these differences, there is no strict dividing line between implicit learning and implicit memory. For example, Graf and Schacter’s (1985) demonstration of implicit memory for novel associations between words in both normal and amnesic patients is similar to implicit learning of covariations. Implicit memory for novel visual forms (Muscen & Treisman, 1990; Schacter, Cooper, & Delaney, 1990) involves nonverbal stimuli and, possibly, some of the same mechanisms as implicit learning of visual concepts. In the section on conceptual fluency, the similarities between the mechanisms underlying perceptual fluency (an implicit memory measure dependent on priming) and conceptual fluency (a measure of implicit learning) are discussed. Berry and Dienes (1991) identified five general characteristics that implicit memory and implicit learning have in common: Both are preserved in amnesia, both are independent of explicit learning, both are more durable than explicit learning, both are tied to surface characteristics, and neither is affected by variations in type of study processing. Although the first three similarities remain well supported, some studies imply that implicit learning may be tied to surface characteristics (see the Representation of Implicit Knowledge section) and that it is affected by variations in type of study (see the Automaticity of Implicit Learning section).

Procedural memory refers to memory for how to carry out processes. There are many definitions of procedural memory; Roediger (1990) claimed to have counted three or four distinct meanings of the term. Depending on the definition used by each theorist, implicit learning may overlap well or less well with what he or she considers to be procedural memory. However, one definition of procedural memory decidedly does not involve implicit learning: procedural memory as the compilation of explicit declarative knowledge into nonconscious procedures. This is the definition used by Anderson (1987), who called the nonconscious procedures resulting from the compilation “cognitive skills.” This sort of procedural memory is not implicit learning because implicit learning does not involve explicit knowledge at the outset. Subjects may develop explicit knowledge in parallel with their implicit knowledge, but the latter is not a consequence of the former (parallel development of the two types of knowledge is discussed in more detail later).

Squire, Knowlton, and Musen (1993; Squire, 1992) included implicit learning processes in two categories of nondeclarative memory that they called “skills” and “habits.” Skills are procedures for operating in the world and are of three types: motor, perceptual, and cognitive. The tasks they included within this group are implicit learning tasks that use what is referred to in this article as efficiency or prediction response modalities, such as dynamic systems learning and the serial reaction time task. Habits are “dispositions and tendencies that are specific to a set of stimuli and that guide behavior” (Squire et al., 1993, p. 471). The tasks that Squire et al. included in this group are those that customarily use what is called here the conceptual fluency response modality (e.g., artificial grammar learning and visuospatial concept learning). Therefore, implicit learning includes

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**Table 1**

*Comparison of Implicit Memory and Implicit Learning*

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<thead>
<tr>
<th>Feature</th>
<th>Implicit memory (priming)</th>
<th>Implicit learning</th>
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<tbody>
<tr>
<td>Knowledge gained</td>
<td>Verbatim stimulus (sometimes associations)</td>
<td>Novel pattern or rule</td>
</tr>
<tr>
<td>Stimuli</td>
<td>Usually verbal</td>
<td>Usually visual or visuospatial</td>
</tr>
<tr>
<td>Role of awareness</td>
<td>Not required</td>
<td>Possibly required</td>
</tr>
<tr>
<td>Role of attention</td>
<td>Minimal</td>
<td>Important</td>
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both habits and skills. Within the domain of skills, implicit learning cuts across the distinctions among perceptual, motor, and cognitive skills, including tasks from each that involve learning patterns or rules that exist in the stimuli and excluding tasks that do not. For example, in studies of learning to apply an equation (Charness et al., 1988; Milberg et al., 1988) or perceptual motor skills such as learning to read reverse script (N. J. Cohen & Squire, 1980; Moscovitch, Winocur, & McLachlan, 1986), it is unclear what is involved in the skill subjects are learning. Kosslyn and Koenig (1992) suggested that mirror reading might involve a process in which the sight of familiar reversed words leads subjects to scan right to left rather than left to right, and in that way improves their ability to read words. If this is the case, subjects are clearly not learning novel information about structured stimuli in mirror reading, and, therefore, mirror reading is not considered an implicit learning task here.

Mishkin et al. (1984) and Sherry and Schacter (1987) identified similar systems that they called “habit learning” and “System 1” learning, respectively. Both identified this system as performing gradual, incremental learning as opposed to “memory” or “System 2,” which is involved with recording episodic details. Sherry and Schacter suggested that the two memory systems evolved because they were functionally incompatible: System 1 detects and preserves invariants over time, discarding extraneous details, whereas System 2 saves contextual details. Implicit learning, at first glance, seems to overlap well with habit or System 1 learning. Both are gradual types of learning in which information is acquired that can be generalized to novel situations. However, although implicit learning appears to develop gradually, it is still an empirical question how quickly implicit knowledge can be gained. Much of the research in habit learning has been performed on animals, and it is unclear at present how well the distinction applies to human beings.

Finally, implicit has a somewhat different meaning in the area of developmental psychology, in which it is used to characterize all of the innate structures and preverbal procedures that underlie development in perception, language, and other areas of cognition (Gelman, 1991; Kamiloff-Smith, 1986, 1990). For example, Gelman (1991) considered preverbal skeletal counting and arithmetic principles to be implicit procedures used in the development of mathematical knowledge. In this article, implicit learning is limited to situations in which subjects learn novel information about new stimuli and is agnostic as to whether the mechanisms within implicit learning are innate or constructed.

Stimulus Structure and Response Modalities

Nine different learning paradigms fit the criteria for implicit learning discussed earlier. The differences between them can be usefully illuminated by examining two properties of these tasks: the structure of the stimuli presented to subjects and the response modality, or dependent measure, involved. As shown in Table 2, the tasks fall into three stimulus types and three response modalities. The three stimulus types are visual patterns, sequences, and functions. The first response modality is conceptual fluency: Subjects make ratings or classify items, usually reporting that they rely on their intuition or feelings to make such judgments. The second is efficiency: Subjects show that they have induced knowledge by their increased speed or accuracy in processing the information. The third is prediction and control: Subjects demonstrate learning by accurately predicting or controlling some aspect of the stimuli. In the implicit learning research that has been performed to date, stimulus type and response modality tend to covary, with visual concepts being tested through conceptual fluency, sequences through efficiency, and functions through prediction and control (see Table 2). However, these are not necessary covariations: Any of the stimulus structures could conceivably be taught and evaluated through any of the response modalities. For example, Cleermans and McClelland (1991) taught subjects sequences from an artificial grammar in a serial reaction time paradigm, and Roussel, Mathews, and Druhan (1990) taught grammar strings with a Hebb digits task paradigm.

This section begins with a presentation of each of the implicit learning research areas, describing for each of the stimuli, the usual experimental methodology, and evidence concerning how well it meets the definition of implicit learning proposed. After the presentation of the research areas, the similarities and differences between the different stimulus structures are analyzed in more detail, including consideration of what stimulus factors, such as complexity, may make a stimulus type suitable for being learned implicitly without being easily learned explicitly. Finally, a fuller treatment of the properties of each of the different response modalities is provided, including a discussion of their underlying mechanisms and independence.

Several of these areas of study have been classified by the researchers involved as implicit learning, and they all clearly meet the criteria presented in the introduction. That is, implicit learning involves learning complex information in an incidental manner without sufficient verbalizable knowledge of the rules or pattern learned to account for performance, and such learning is preserved in amnesia. These areas include artificial grammar learning, covariation learning, serial reaction time, contingent reaction time, puzzle learning, and dynamic systems. Other tasks have not been classified as implicit by the researchers involved but still meet the criteria on the basis of information presented in published articles.

Overview of Implicit Learning Tasks

Artificial grammars In studies of artificial grammar learning, subjects typically study 15–25 letter strings produced by an artificial grammar. Subjects usually memorize groups of strings to a criterion but also can merely observe strings (A. S. Reber & Allen, 1978) or rate strings for pleasantness (McAndrews & Moscovitch, 1985). Subjects become better at memorizing strings as this learning phase progresses, suggesting that induced regularities may be facilitating learning (G. Miller, 1958; A. S. Reber, 1967). In most experiments, subjects then evaluate whether novel strings are grammatical, usually achieving performance levels of 60%–80% correct (A. S. Reber, 1989). Subjects show partial but inadequate ability to verbally report rules followed by the stimuli (Mathews et al., 1989; A. S. Reber, 1989) and sometimes report invalid rules (A. S. Reber & Lewis, 1977). Amnestic is unimpaired in regard to making grammaticality judgments about novel strings (Knowlton, Ramus, & Squire, 1992).
Table 2

<table>
<thead>
<tr>
<th>Stimulus structure</th>
<th>Conceptual fluency</th>
<th>Efficiency</th>
<th>Prediction and control</th>
</tr>
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<tbody>
<tr>
<td>Visual</td>
<td>Artificial grammars</td>
<td>Artificial grammars</td>
<td>Contingent response</td>
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<tr>
<td>Sequence</td>
<td>Visuospatial concepts</td>
<td>Covariation learning</td>
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<tr>
<td>Function</td>
<td></td>
<td>Serial reaction time</td>
<td>Function matching</td>
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<td></td>
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<td>Contingent response</td>
<td>Dynamic systems</td>
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<td></td>
<td></td>
<td>Hebb digits</td>
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<td>Puzzle learning</td>
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<td></td>
<td></td>
<td>Motor learning</td>
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**Visuospatial concepts.** Visuospatial concept learning studies use two types of stimuli. In one, concepts have ill-defined features; concept exemplars are formed by distorting prototypes, such as dot patterns (Homa, 1979; Posner & Keele, 1968) or colored squares within a grid (Fried & Holyoak, 1984). In the other type, concepts have well-defined features; exemplars have discrete features that are varied on two or three dimensions (Estes, 1986; Kemler Nelson, 1984; Medin, Dewey, & Murphy, 1983) or features that vary in the probability that they are present or absent (Carlson & Dulaney, 1985; Rosch & Mervis, 1975). In some studies, subjects study a set of exemplars from one or more concepts and then classify novel exemplars, similar to the method of artificial grammar studies (Carlson & Dulaney, 1985; Posner & Keele, 1968). Other studies have subjects decide the concept to which each stimulus belongs; subjects then receive feedback, thus combining learning and testing into one process (Estes, 1986; Fried & Holyoak, 1984; Kemler Nelson, 1984; Rosch & Mervis, 1975). Data concerning subjects' ability to verbalize what is learned are rarely presented in these studies; Posner and Keele (1968) found that subjects often report no rules, and the rules that are reported are individual and highly idiosyncratic. Knowlton and Squire (1992) showed normal dot pattern prototype learning in amnesic subjects.

**Covariation learning.** The studies in this group all show implicit learning of a covariation between features within visual stimuli or between a feature of visual stimuli and a verbal label. For example, Lewicki (1986) presented pictures of women paired with verbal descriptions of their personality and found that subjects learned a covariation between hair length and personality traits. The covariations used are usually simple but, nevertheless, are not detected explicitly by the subjects, probably because they are theoretically improbable (such as the covariation between hair length and personality traits; Lewicki, 1986), because they involve very small perceptual alterations in the stimuli that are not salient to the learner (Lewicki, Hill, & Sasaki, 1989), or because the stimuli are presented only for brief amounts of time (Musen & Squire, 1993). These studies often use the efficiency response modality: In Lewicki's (1986) study, subjects answered questions that were relevant to the covariation more slowly than irrelevant questions; in J. Miller's (1987) study, subjects identified a centrally located letter more quickly when it was correlated with flanker letters. Other studies have used the conceptual fluency response modality, in which subjects learn to classify the stimuli into different categories based on the covariation (Hill et al., 1989; Lewicki et al., 1989). Musen and Squire (1993) have found normal covariation learning in amnesic subjects using a Stroop paradigm; subjects became faster at naming the color of ink in which a stimulus word was presented when the ink color and word identity were covaried.

**Serial reaction time task.** Serial reaction time (Nissen & Bullemer, 1987) is a straightforward task in which subjects make a simple response to each stimulus presented, usually by pushing a button corresponding to a stimulus light (but also by pairing verbal stimuli and responses; Hartman, Knopman, & Nissen, 1989). In most experiments, the lights appear in a set sequence of 10 positions. Learning of the sequence is measured by the difference in reaction time between conditions in which the stimuli appear in a pattern and conditions in which they are presented randomly. Although some subjects do become aware of the sequence during learning, aware and unaware subjects both show a pattern of reaction time decrease (Willingham, Nissen, & Bullemer, 1989), indicating that implicit learning can occur independently of awareness; however, aware subjects show a greater reaction time decrease than do unaware subjects. Amnestic learn and maintain their knowledge of this task normally (Nissen & Bullemer, 1987; Nissen et al., 1989).

**Contingent response task.** In a contingent response task, subjects make a response to a particular sequence item that is contingent on the previously presented items. The response measured is usually reaction time for locating a stimulus in a matrix, in which the position is dependent on previous events (Lewicki et al., 1987; Lewicki, Hill, & Biziot, 1988; Perruchet, Gallego, & Savy, 1990). An alternative response measure is accuracy of prediction of the location of the next item (Kushner, Cleeremans, & Reber, 1991). For example, in Lewicki et al.'s (1988) study, subjects searched for and reported the location of a target on each trial. The trials were (unbeknownst to the subjects) broken into blocks of five, in which the position of the stimulus in the last three trials was predictable from the position in the preceding two trials. Subjects showed decreased reaction time across trials and, when the contingencies were changed, an overall increase in reaction time that was proportionally greater.
in the predictable trials in each block. In all such studies, subjects are unaware of the existence of the pattern and unable to verbally describe it. In a related paradigm—probability matching studies in which subjects are asked to predict which of two events will occur next and are trained by feedback—subjects can learn to track a sinusoidal (F. W. Young, 1967) or sawtooth pattern (A. S. Reber & Millward, 1971) and can learn contingent events with lags of up to five intervening trials (Millward & Reber, 1972). No one has reported testing amnesics to determine whether they can learn this type of task.

**Hebb digits task.** The Hebb digits task (Hebb, 1961) requires subjects to echo (either vocally or through writing or typing; Cunningham, Healy, & Williams, 1984; Hendrich et al., 1991) digit strings in a series in which every third string is identical. Learning is defined as increased accuracy on the repeated string as compared with the nonrepeated strings. The Hebb effect remains effective for up to five intervening trials (Melton, 1963), and the size of the effect decreases as list similarity increases (Melton, 1964); changing the first two digits (but not any other digits) eliminates the repetition effect (Schwartz & Bryden, 1971), and the effect does not occur if the grouping of digits is changed (e.g., 432 as “forty-three, two” and then “four, thirty-two”; Bower & Winzenz, 1969). Subjects who are unaware of the repetition show the same pattern of results as subjects who become aware of the repetition during the course of the experiment (McKelvie, 1987). Saddeley and Warrington (1970) found normal performance for amnesics on this task with strings varying in length from five to eight letters, but Charness et al. (1988) and Milberg et al. (1988) found no learning in amnesia given strings longer than their digit span.

**Puzzle learning.** Learning patterns of moves in puzzles like the Tower of Hanoi over repeated solutions is similar to motor learning and other sequence learning tasks and, hence, a good candidate for implicit learning; however, because puzzle learning may require explicit in addition to implicit learning, some researchers have rejected puzzles as an area of implicit learning (Squire & Frishman, 1990). P. J. Reber and Kotovsky (1992) argued that the Tower of Hanoi, which has been used in most previous studies, emphasizes explicit solution processes over implicit learning of patterns of moves but that other puzzles may be appropriate for demonstrating implicit learning. They developed a linear solution space puzzle, the Ball and Boxes problem, that they argued is more amenable to implicit learning of a solution than the Tower of Hanoi because the rules underlying the problem are not explicitly accessible to subjects. They found that subjects learned to solve this problem without gaining verbalizable knowledge about the solution.

Initial studies of amnesics, including HM, indicated that they showed learning on the Tower of Hanoi across repeated solutions if they were prompted to stay on the optimal solution path (N. J. Cohen, Eichenbaum, DeAceto, & Corkin, 1985); however, this result was not replicated with Korsakoff’s amnesics (who may have been hampered by the frontal aspects of Korsakoff’s syndrome; Butters, Wolfe, Martone, Granholm, & Cermak, 1985). Gabrieli, Keane, and Corkin (1987) restated HM on the Tower of Hanoi without prompting and found poor overall retention. However, HM did show mastery of certain portions of the puzzle that he had encountered in the efficient solutions on which he had been trained earlier, and he showed improvement on repeated solutions of the Missionaries and Cannibals problem (as did two other amnesics). Interestingly, he was worst in sections of the puzzle not usually encountered in efficient solutions. These studies imply that amnesics without frontal involvement may show learning of the patterns of moves necessary for solution of a puzzle but not general strategies or explicit knowledge of how to solve the particular puzzle.

**Motor learning.** Many experiments in the motor learning field have investigated the ability of subjects to learn particular patterns in tracking tasks (Franks, 1982; Frith & Lang, 1979; Pew, 1974) or contingent relations between presented stimuli and movements (T. D. Green & Flowers, 1991). In all of these cases, subjects did not have good verbal knowledge of the patterns they had learned or even that there was a pattern. As in serial reaction time, learning is measured through the efficiency response modality by comparing performance on patterned stimuli with performance on random stimuli. Amnesics show normal learning and maintenance of tracking of a pursuit rotor (Brooks & Baddeley, 1976; Cermak, Lewis, Butters, & Goodglass, 1973; Corkin, 1968) and of bimanual tracking (Corkin, 1968); however, it is unclear at present whether they can learn a specific pattern, as opposed to these general skills.

**Function matching.** In function matching learning, subjects learn to produce a desired value of a variable matching one or more given variables, in which the underlying relationship between the variables is a mathematical function. Subjects are presented with a stimulus that includes the given variable(s), make a response, and are given feedback (Deane, Hammond, & Summers, 1972; Hammond & Summers, 1965; Koh & Meyer, 1991; Price, Meyer, & Koh, 1992; Summers & Hammond, 1966). For example, Koh and Meyer (1991) taught subjects a functional relationship between a length of a line and a length of time; subjects were presented with the line segments as stimuli; responded by indicating a time interval (by making two consecutive key presses), and received feedback as to how well their response matched the desired value. None of these studies have reported data pertaining to subjects’ awareness of the functional relationships; in addition, no reported research has investigated how well amnesics can perform function learning.

**Dynamic systems.** Dynamic systems learning (Berry & Broadbent, 1984, 1988; Broadbent, FitzGerald, & Broadbent, 1986) requires subjects to control the value of a particular variable by manipulating another variable. For example, in Berry and Broadbent’s (1984) study, subjects manipulated the size of the work force in a factory to control the amount of sugar output by the factory. The variables are related by an equation, which, in Berry and Broadbent (1984), was Production = 2 × Work Force − Production on Last Trial, plus a random factor. In most cases, subjects are asked to manipulate simulated systems for which they have strong preexisting mental models so as to study the interaction of implicit and explicit learning; subjects show explicit knowledge that is independent of and can differ greatly from their performance ability, and they are unaware of the discrepancy. Amnesics show normal learning but do not maintain their knowledge over a 1-month break, whereas normal subjects do (Squire & Frishman, 1990).

**Related tasks: Frequency and probability learning.** Frequency monitoring and two-event probability learning have been considered by some (A. S. Reber, 1989) to be implicit
learning, but they do not meet all of the criteria presented here. They do, however, meet two of these criteria: They are learned incidentally (A. S. Reber, 1989; Zacks, Hasher, & Sanft, 1982) and are preserved in amnesia (Sagar, Gabrieli, Sullivan, & Cor- kin, 1990). The information learned may or may not be verbalizable. In frequency monitoring, subjects must be able to verbalize; in two-event probability learning, however, they need not. In addition, these tasks are similar to implicit learning in that the degree of learning is dependent on attention and processing in working memory (Kellogg & Dowdy, 1986; Sanders, Gonzalez, Murphy, Liddle, & Vitina, 1987), and the tasks appear to be based on processes different from those in explicit memory (Hintzman, Curran, & Oppy, 1992; Vakil, Galek, Soroker, Ring, & Gross, 1991). However, they are excluded from implicit learning here because the information learned is relatively simple: Subjects merely calculate the absolute frequency of each item or the relative frequencies of two items. There is no knowledge of covariations of stimuli or any of the other more complex structures that are learned in implicit learning. Nevertheless, frequency and probability learning may share some mechanisms with implicit learning and are discussed when relevant.

**Stimulus Structure**

The structure of the stimuli used in implicit learning tasks can be compared on several levels. First, each can be described in terms of the abstract mathematical formalism on which it is based. For example, an artificial grammar is formalized as the finite state automation that produces it (Chomsky & Miller, 1958); visuospatial concepts can be formalized in terms of the mathematical distance of exemplars from the prototype; dynamic systems can be formalized in terms of the underlying formula relating the variables; and patterns in the serial reaction time task can be formalized in terms of the degree of statistical structure they show (Stadler, 1992). However, there are problems with using only mathematical formalisms to describe stimulus structure. First, there is no guarantee that subjects are actually learning the mathematical structure; for example, in artificial grammars, there is evidence that subjects learn personal, idiosyncratic grammars that correlate with the actual grammar but are not identical to it (Dulany et al., 1984). Second, the relative complexity of two stimulus structures based on their mathematical formalisms does not necessarily predict which will be easier to learn. For example, subjects show a bias toward learning power functions rather than mathematically simpler linear functions in some circumstances (Koh & Meyer, 1991). Third, the same underlying structure can be instantiated in different surface forms that may be learned differently. For example, artificial grammars presented as visual letter strings appear quite different from artificial grammars presented as a series of dot locations (Cleeremans & McClelland, 1991; Manza & Reber, 1992) or as strings in a Hebb task (Roussel et al., 1990), and they may be learned in different ways.

Given that the mathematical formalism of the structure is not sufficient to account for its psychological processing and representation, what are some other ways to compare stimulus structures that might shed light on how they are learned? One important factor that inspired the division of implicit learning tasks into visual concepts, sequences, and functions is how the stimuli are structured in time and space. Visual concepts are presented as integrated stimuli in time. Subjects may make inductions from stimuli presented at different times, but the key features of each stimulus are always simultaneously present. Sequences, on the other hand, are distributed in time: Subjects are presented with a series of locations or objects, each presented at a different time, and learn the pattern itself or covariations among pattern elements. Function learning involves learning a relationship between variables that appear at different times. Stimulus structure types also differ in how they use space. Visual concepts usually have features distributed spatially, and relative spatial position is an important part of the structure. Likewise, many examples of sequence learning involve spatially separate stimulus locations, as in the serial reaction time task, the contingent response task, puzzle learning, and motor learning. The Hebb digits task, however, does not involve spatial elements. Function learning may include spatial elements but usually does not in the case of dynamic systems.

Another factor is the sensory modality used. Most implicit learning studies use visual material, although Manza and Reber (1992) presented artificial grammar strings auditorily and Lewicki and colleagues (Lewicki, 1986; Lewicki et al., 1989) paired their visual stimuli with auditorily or visually presented verbal descriptions. Although the lower spatial resolution of the auditor input system precludes auditory analogs of most visual concepts, there is no reason that auditory stimuli cannot be used in sequence or function learning tasks. Tactile stimuli could also be used in spatially or temporally structured stimuli.

All stimulus structures are in some way complex enough that subjects do not gain sufficient explicit knowledge of the pattern to account for their performance. This is not to say that implicit learning mechanisms cannot cope with simple patterns but merely that simple patterns lend themselves to explicit knowledge, either through spontaneously noticing the pattern or conscious hypothesis testing; therefore, it is methodologically impractical to study implicit learning of simple stimuli in normal humans. The stimuli used in implicit learning are complex in different ways. Perhaps the most important contributor to complexity is the number of rules that a subject must learn; the greater the number, the greater the complexity. Buchner and Funke (1993) described how the complexity of finite state automata, used in artificial grammar research and their dynamic systems research, can be analyzed in terms of the number of states and connections between them. The number of variables to be processed also contributes to complexity; implicit learning appears to involve the processing of a larger number of variables than explicit learning (Broadbent et al., 1986; Hayes & Broadbent, 1988). In some situations, complexity may help implicit learning if the complexity leads to greater systematicity or redundancy in the rules. Billman (1989; Kersten & Billman, 1992) showed that systematicity helped subjects learn under implicit conditions.

However, factors other than the sheer quantity of rules or variables make stimuli difficult to learn explicitly without eliminating implicit learning. One such factor is the presence of irrelevant random stimuli (Kushner et al., 1991; Lewicki et al., 1987). The explicit thought system has difficulty determining which stimuli are random and should be ignored, but implicit learning
appears to be less affected, perhaps because it can calculate dependencies among a larger number of variables than explicit thought. A second potential contributor is indeterminacy. Artificial grammars are indeterminate in that, at each state, there is more than one possible subsequent state. Garner (1962) reviewed research concerning the deleterious influence of stimulus uncertainty on explicit learning. A third contribution is made by random noise. Bruner, Wallach, and Galanter (1959) found that, in explicit sequence learning, a few errors in the sequence greatly harmed subjects' ability to learn the sequence; however, implicit learning of artificial grammars by means of the efficiency response modality can occur even when there are occasional incorrect elements (Cleeremans & McClelland, 1991). Fourth, an important role is played by the ability to parse the stimulus into meaningful pieces. In serial reaction time, for example, the sequence is probably hard to learn explicitly because the boundary between the end of the sequence and the beginning of the next repetition is not marked. Similarly, implicit learning of multiple concepts simultaneously is greatly hampered if subjects are not told the concept to which each stimulus belongs, except when the concepts consist of low distortion exemplars that do not overlap (Fried & Holyoak, 1984; Homa & Cultice, 1984).

Finally, a role is played by the salience of the rule to explicit thought. Covariation learning, as investigated by Lewicki and colleagues (Lewicki, 1986; Lewicki et al., 1989), typically uses fairly simple relations (e.g., hair length and kindness); however, the relations are not discovered by explicit thought as a result of their lack of saliency, either because the relation is not theoretically plausible or because the difference in the perceptual feature is very small between the two groups. Similarly, salience plays an important role in determining how well subjects will gain explicit knowledge in dynamic systems learning (Broadbent et al., 1986). It is important to keep in mind that implicit learning is probably not impervious to the effects of these factors; it may well be harmed by them, but to a lesser degree than explicit thought. A better understanding of how explicit and implicit learning are affected by the factors just described awaits further research.

Response Modalities

There are three types of dependent variables, called response modalities, through which subjects can demonstrate learning in implicit learning research: conceptual fluency, efficiency, and prediction and control. This section first examines each response modality separately, identifying some of the representations and processes that may be involved in each. It then addresses whether the information gained by each response modality is transferable to others. The presence or absence of transfer indicates the degree to which the response modalities share processes and representations. Finally, the development of explicit learning, which in itself can be seen as another response modality, is briefly discussed.

Conceptual fluency. The conceptual fluency response modality includes all of the implicit learning tasks in which subjects are asked to make judgments about novel stimuli on the basis of implicit knowledge that they have abstracted from earlier study of related stimuli. In most artificial grammar studies, the judgment involves evaluating novel stimuli for grammaticality, and, in visuospatial concept learning tasks, it involves classifying novel exemplars. In both cases, subjects are able to make these judgments, but they report that they do not use explicit rules or other guidelines for making their decisions; rather, they depend on their intuitions or feelings of knowing about the stimuli (A. S. Reber, 1989; A. S. Reber & Allen, 1978). Judging based on these intuitions or feelings of knowing is called conceptual fluency by analogy to Jacoby and Dallas's (1981) “perceptual fluency,” which refers to the ability of subjects to evaluate how easily a stimulus was processed by their perceptual systems and to use this knowledge in making judgments about the stimulus. Conceptual fluency refers to a similar ability to evaluate the processing of the novel stimulus to make judgments concerning its status with regard to previously learned conceptual knowledge.

The types of judgments that can be performed on the basis of conceptual fluency are varied: In artificial grammar learning, subjects are usually asked to make decisions about the grammaticality of stimuli; in visuospatial concept learning, they are usually asked to decide into which of two previously learned concepts a novel exemplar should be classified. A related judgment that appears to be evaluated through conceptual fluency and sensitive to the same knowledge base as grammaticality judgments is an affective rating of a stimulus. The mere exposure effect is the finding in many domains that subjects prefer previously encountered items to novel items. Gordon and Holyoak (1983) showed that subjects liked novel grammatical strings and visuospatial patterns better than novel nongrammatical ones after learning a set of grammatical patterns and that their judgments of liking were related to their judgments of grammaticality. In addition to grammaticality judgments, classification, and affective judgments, conceptual fluency can be attributed to other factors. For example, Franks (1982) found that subjects who were unaware of the existence of a pattern in a visual tracking task reported that they believed that the task was slower toward the end than at the beginning, implying that they recognized that the task was easier for them but attributed it to changes in the task rather than changes in themselves from learning.

If so many different judgments can be made on the basis of conceptual fluency, is it possible that conceptual fluency can be used as a basis for recognition judgments as well? There has been some controversy over whether people can use perceptual fluency as a basis for recognition judgments (Haiet, Shimagura, & Squire, 1992; Hirst, Johnson, Phelps, & Volpe, 1988; Johnson, Hawley, & Elliott, 1991), but the differences in results found may be due to the explicit expectations of the subjects as to what are legitimate bases on which to make judgments. As Jacoby and Dallas (1981) have pointed out, subjects may have a bias toward using episodic recognition as the basis for recognition judgments because it is more reliable. Most people consider recognition to involve recall of particular episodic instances of the stimulus; they are unlikely to base recognition on perceptual or conceptual fluency alone unless they realize that is what the experimenters actually want them to do. Evidence implying that recognition judgments can, in some circumstances, be made on the basis of conceptual fluency comes from a study of
artificial grammar learning in amnesics and normal subjects (Knowlton et al., 1992). Normal subjects performed better on recognition and similarity judgments than grammaticality judgments, but the amnesics achieved average scores on the three tasks that were statistically indistinguishable. Given amnesic subjects' deficits in episodic memory, they may have been using conceptual fluency as the basis for recognition and similarity as well as grammaticality judgments. Additional evidence comes from a study conducted by Fendrich et al. (1991), who found that recognition of strings in a Hebb task was related to efficiency of typing the strings when the recognition judgments were made after the string was typed, implying that the subjects may have been relying on the fluency of typing the string as a basis for their recognition judgments.

In a broader sense, whether fluency information is used in making any kind of judgment depends on subjects' attribution of the fluency and willingness to use fluency as a valid basis for that type of judgment. Bornstein (1992) proposed a theory of perceptual fluency use in making affective ratings or recognition judgments of stimuli that were previously subliminally presented (known as the subliminal mere exposure effect). He postulated an explicit process that can attribute fluency either to recognition of the stimulus or to liking of the stimulus. In many implicit learning studies using the conceptual fluency response modality, subjects are told to make judgments any way they can, and, on occasion, they are explicitly told to rely on their instincts. Therefore, it is not surprising that subjects believe that conceptual fluency is a legitimate basis for these judgments and are willing to attribute such fluency to their knowledge of the pattern. Lewicki et al. (1989) found that subjects could learn a covariation when told to differentiate between intelligent and unintelligent brain scans but not when told to differentiate between Type A and B brain scans. It is possible that subjects in the intelligence condition were willing to use conceptual fluency but that subjects in the categorization condition believed they should use explicit information and disregarded conceptual fluency.

Reliance on conceptual fluency as a basis for judgments, including recognition, may be learned over time, so that more practiced subjects may show a greater reliance. This time course makes sense if one considers that people are seldom asked in school or work situations to rely simply on their intuition and that subjects therefore would be unused to making judgments in this way. Merikle and Reingold (1991) found that an indirect task (evaluating contrast between the word and background mask) was initially more sensitive than a direct task (deciding whether the word was old or new) in an experiment of memory for subliminally presented words but that the direct task became more sensitive than the indirect task over trial blocks. Similarly, G. Mandler, Nakamura, and Van Zandt (1987) found that recognition of previously subliminally presented geometric forms increased over testing trial blocks, whereas affective judgments of the same forms decreased over blocks. According to Bornstein's (1992) theory of the mere exposure effect, the latter may be a result of the former. Subjects come to attribute conceptual fluency to recognition rather than to their liking of the stimulus. In a meta-analysis of a series of subliminal mere exposure effect studies, Bornstein found that the longer the delay between presentation and testing, the greater the difference between affective and recognition judgments. Lewicki et al. (1989) also found that subjects improve in their ability to use implicitly learned information over trials, a process they called self-perpetuating development of encoding biases. Interestingly, this increase occurs even when neutral stimuli with no covariation present are used, leading to the odd situation of the effect strengthening while the evidence for it weakens.

What are some potential mechanisms underlying conceptual fluency? Conceptual fluency appears to require two processes: a change in the fluency of processing of the stimuli and an evaluation process that takes the fluency information and makes a judgment based on it. In the Neural Substrates of Implicit Learning section, it is suggested that the association areas are the location of changes in fluency and that the frontal lobes play a role in the evaluation process. What kinds of representational change are involved in implicit learning accessed by conceptual fluency? The changes involved in perceptual fluency are based on priming (Jacoby & Dallas, 1981); easier processing is assumed to result from increased activation in the processing components. Schacter et al. (1990) argued that implicit memory for visual figures depends on priming in a structural representation system. Implicit learning could similarly depend, in part, on priming in high-level response programming systems or high-level relational processing systems. Implicit learning that results in conceptual fluency knowledge therefore may come about in three stages. First, during the time of stimuli presentation and study, priming other changes occur in these high-level systems. Second, these changes allow subjects to process more fluently novel related stimuli. Third, the quality of processing is, at least with practice, consciously available to subjects, who can use it to make judgments. A possible difference between conceptual fluency and perceptual fluency is that the former may be based on higher level mechanisms as well as perceptual mechanisms and may involve more complex changes in the system than simple priming.

**Efficiency**: The efficiency response modality involves the evaluation of implicit learning through the changed speed or accuracy with which subjects respond to stimuli. Work using this dependent measure includes most of the research that has been performed in the area of sequence learning, including the serial reaction time task, the contingent response task, the Hebb digits task, puzzle learning, and motor learning. It also includes covariation learning of the sort studied by Lewicki (1986). It is unclear at this point whether efficiency improvement is caused by changes in high-level response programming systems, perceptual systems, or a combination of the two.

That learning is linked to response programming is supported by research in brain-damaged populations and normal humans. Serial reaction time task learning is impaired in patients with Huntington's disease (Knopman & Nissen, 1991) and Parkinson's disease (Ferraro, Balota, & Connor, 1993), which both affect a part of the brain, the basal ganglia, that is primarily involved in motor behavior. Cunningham et al. (1984) found the Hebb digits effect only when subjects responded to each digit string; if subjects were merely shown the string, there was no effect. J. Miller (1987) found that the cue in his correlational cuing experiment operated primarily or possibly exclusively by activating the response (yes or no) rather than by priming a particular target that, in turn, was associated with
a response. Willingham et al. (1989), in a study using the serial reaction time task, decoupled the spatial pattern of the stimuli from the spatial patterns of the motor responses by having subjects respond to the color of the stimulus rather than its position. Subjects learned if the motor component alone was spatially structured (i.e., if the colored dots flashed such that there was a regular sequence in the button presses) but did not learn if the visual stimuli alone were spatially structured (i.e., if there was a regular sequence in the locations of the colored dots). Learning in response programming systems must occur at a relatively high level, higher than the level of motor effector selection, because transfer of learning between specific motor effectors has been shown in the serial reaction time task (A. Cohen, Ivry, & Keele, 1990; Keele, Cohen, & Ivry, 1990).

A study conducted by J. H. Howard, Mutter, and Howard (1992) provides evidence that learning is primarily perceptual in the serial reaction time task. They found that subjects who merely observed the stimuli flashing without responding to them showed the same amount of learning of the pattern when transferred to the response task as subjects who were responding throughout the experiment. However, subjects who observed had more explicit knowledge of the sequence than did those in the response group, as shown by a sequence generation task, and therefore their performance may have been partially reliant on explicit knowledge rather than implicit knowledge. In addition, Stadler (1989) found that perceptual alternations in stimuli were more disruptive of learning than motor response alterations, implying the involvement of perceptual mechanisms in learning.

Fendrich et al. (1991) found evidence for learning in both perceptual and motor systems in a Hebb digits typing task. They found that performance both on lists of old digits coupled with new responses and on new digit lists coupled with old responses was better than performance on lists in which both the digits and the responses were new. In conclusion, there is not enough evidence at present to determine whether implicit learning in the efficiency response modality is subserved by motor processing or perceptual processing. The mixed evidence implies that there may be a combination of perceptual and motor knowledge shown in efficiency. In addition, A. Cohen et al. (1990; Curran & Keele, 1993) have shown that two mechanisms are involved in serial reaction time learning of sequences: a nonattentioin pairwise associator that learns relationships between adjacent items and an attentional hierarchical mechanism that learns higher order information about the sequence. These two mechanisms are discussed in more detail in later sections, but it should be noted here that they may be differently dependent on perceptual and motor processes.

Prediction and control. Prediction and control is the response modality involved when subjects demonstrate learning by an increased ability to predict subsequent stimuli or to control the values of variables. This response modality is used in research on function matching learning, in which subjects, given a value on a variable not under their control, produce the correct value of a second variable under their control (Koh & Meyer, 1991). It is also involved in dynamic systems learning, in which subjects control the value of a variable they cannot directly manipulate by choosing an appropriate value for a variable they can manipulate (Berry & Broadbent, 1984, 1988). Finally, prediction and control are involved in the contingent response task used by Kushner et al. (1991), in which subjects predict the location of the subsequent stimulus, and in contingent probability learning tasks (Millward & Reber, 1972; A. S. Reber & Millward, 1971; F. W. Young, 1967) in which subjects predict which of two stimuli will occur next.

There has been little research performed in this response modality that allows it to be conclusively situated with respect to the other response modalities. As in the case of efficiency, prediction and control may include elements strongly associated with high-level response programming. Conversely, prediction and control may rely on perceptually based knowledge and may involve a process of using conceptual fluency knowledge for each of the possible responses in choosing one that “feels right.” In addition, prediction and control may lead to more explicit knowledge than the other two response modalities, because one has to make an explicit choice as to what item is coming next or what item can lead to the desired goal. In dynamic systems research, subjects develop implicit knowledge of the system without accompanying explicit knowledge (Berry & Broadbent, 1984, 1988; Broadbent et al., 1986); however, in tasks involving simpler patterns, such as the serial reaction time task, subjects may not be able to learn to predict without also gaining significant explicit knowledge of the sequence (this possibility is discussed further in the following section). In short, a better understanding of the mechanisms underlying prediction awaits better understanding of the development of implicit knowledge in the other response modalities and the development of explicit knowledge in implicit learning tasks.

Transfer between response modalities. Is knowledge about a stimulus structure gained through one response modality accessible to a different response modality? If so, there should be transfer of learning between response modalities. Transfer in this sense is important because it allows investigation of the extent to which the mechanisms and representations used in each response modality are dependent or independent. Note that this kind of transfer is different from transfer between related stimuli (discussed further in the section on representation of implicit knowledge); in the case of transfer between response modalities, the stimulus structure is the same but the subject's knowledge of the stimuli is tested through a different response modality. Table 3 summarizes the evidence concerning transfer between response modalities. The empirical evidence is limited; only in the case of transfer from efficiency to prediction and control in the serial reaction time task is there more than one study pertaining to transfer between each combination of response modalities. This section first considers transfer between efficiency and prediction and control and then considers transfer between conceptual fluency and the other response modalities.

Several serial reaction time experiments have tested subjects' ability to generate the sequence after training on the implicit task. In the generation task, subjects are asked, on each trial, to press the button corresponding to where the next stimulus is going to appear rather than the button corresponding to the current stimulus. The generation task is intended to be a measurement of explicit rather than implicit knowledge; it is considered in this section because of its similarity to prediction tasks and the possibility that it taps implicit knowledge, through the pre-
Table 3
Transfer Between and Within Response Modalities

<table>
<thead>
<tr>
<th>Original response modality</th>
<th>Transfer response modality</th>
<th>Prediction and control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conceptual fluency</td>
<td>Visual Sequence</td>
<td>Yes (AG)</td>
</tr>
<tr>
<td></td>
<td>Function</td>
<td>Yes (SRT)</td>
</tr>
<tr>
<td>Efficiency</td>
<td>Visual Sequence</td>
<td>Yes (Hebb)</td>
</tr>
<tr>
<td></td>
<td>Function</td>
<td>Yes (SRT)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Mixed (SRT)</td>
</tr>
<tr>
<td>Prediction and control</td>
<td>Visual Sequence</td>
<td>Yes (CRT)</td>
</tr>
<tr>
<td></td>
<td>Function</td>
<td>Mixed (CRT)</td>
</tr>
</tbody>
</table>

Note. Original training in the conceptual fluency response modality usually involves observation or other nonresponse processing. Cells in brackets represent transfer between different dependent measures within the same response modality. AG = artificial grammar; SRT = serial reaction time; Hebb = Hebb digits task; CRT = contingent response task.

Prediction and control respond to or from conceptual fluency in a very limited ability to predict that is insufficient to account for their performance (Creelman & McClelland, 1991). In a contingent response task, Stadler (1989) found that subjects who showed learning in performing speeded visual search for a target in which the location was contingent on previously presented stimuli did not show any transfer when they were asked to predict where the next target would appear. However, Perruchet et al. (1990) argued that the method used in those studies (asking subjects to make a prediction on each trial) was not a good test of their ability to predict. When they had subjects try to predict with 4–11 targets between successive predictable trials, they found good prediction ability. In sum, the evidence for transfer from efficiency to prediction and control in the serial reaction time task and the contingent response task is mixed; in addition, no studies have investigated transfer from prediction and control to efficiency.

The question of transfer to or from conceptual fluency is more complicated. If efficiency and prediction and control learning turn out to be based on perceptual processing mechanisms, conceptual fluency may tap the same knowledge base, and in that case transfer would be expected. However, even if efficiency and prediction and control prove to be solely based on response programming (or another independent mechanism), apparent transfer from these modalities to conceptual fluency may still be seen for two reasons. First, during efficiency and prediction and control training, stimuli are processed perceptually, and subjects may therefore develop separate knowledge accessible through conceptual fluency in parallel with changes in the response programming mechanisms underlying the efficiency or prediction and control learning. Second, if subjects respond to stimuli during conceptual fluency testing in the same way that they responded during initial learning through efficiency and prediction and control, they may be able to make conceptual fluency judgments based on the fluency of their responses. The latter possibility is supported by research by Fendrich et al. (1991), who found that subjects in a Hebb digits task showed better recognition for a sequence after they had responded to it than before they had responded, implying that they performed recognition at least in part by evaluating the conceptual fluency of the sequence during their response. In conclusion, all of the possible relationships between conceptual fluency and the other two response modalities predict transfer from efficiency and prediction and control to conceptual fluency.

However, when transfer is tested in the other direction (from conceptual fluency to efficiency or prediction and control), the different relationships between the learning mechanisms predict different types of transfer. If learning occurs in separate mechanisms, there should be no transfer; if learning occurs in a common mechanism, then there should be transfer. Dienes, Broadbent, and Berry (1991) conducted an experiment apparently involving the accessibility of artificial grammar knowledge to the prediction response modality. In their sequential letter dependencies test, they presented subjects with truncated strings and asked them whether each possible letter could legally come next in the sequence. However, this test may not measure prediction in the same way as a prediction and control task; rather, it may be performed by imagining each possible letter at
the end of the string and making, for each of these partial strings, a grammaticality judgment.

In conclusion, the study of transfer has promise as a methodology for examining the relationships between mechanisms and representations involved in learning in each of the different response modalities. However, current empirical research is sparse, and it is not possible at this point to make firm conclusions. It should not be forgotten, however, that transfer can occur within a response modality if the task used taps the same knowledge base. Within efficiency, for example, knowledge is transferred between motor effector systems (A. Cohen et al., 1990; Stadler, 1989); within conceptual fluency, knowledge is accessible to grammaticality and affective judgments (Gordon & Holyoak, 1983).

Development of parallel explicit knowledge. This article focuses on implicit learning as distinct from explicit learning. However, in normal humans, it is difficult to develop a pure task that allows only implicit learning to contribute to performance. Using a dual task or other attentional manipulation can interfere with explicit learning, but it also may harm implicit learning (as discussed in the following section). No known dual task interferes only with explicit thought. Presenting stimuli at a rate too fast for conscious thought processes to be brought to bear on them can minimize explicit learning (A. S. Reber, 1989) but, in many tasks, is not practical for investigating implicit learning. Even if subjects are not engaging in conscious hypothesis testing, they can still notice that there is a pattern and develop explicit in parallel with implicit knowledge. Thus, in many of the tasks presented here (e.g., serial reaction time and, to a lesser extent, artificial grammars), subjects show partial verbalizable knowledge of the structure they have learned. It is interesting to speculate about how implicit learning and explicit learning might interact in the same task. It is possible that a certain amount of implicit knowledge can trigger some sort of awareness on the part of the learner that there is a pattern present. The learner can then look for the pattern and gain explicit knowledge of it. Galanter and Smith (1958) observed this pattern of explicit knowledge acquisition in a study of explicit learning of series. They found that subjects would first get a feeling that there was a pattern and then stop and look for it or, alternatively, that they would suddenly just see the structure of the sequence. However, postulating implicit knowledge as a trigger for the development of explicit knowledge implies that a certain amount of implicit knowledge must always precede any explicit knowledge. This is consistent with Stanley, Mathews, Buss, and Kotler-Cope’s (1989) research, which revealed that performance ability in dynamic systems increases earlier than verbalizable knowledge of the task. However, it is not consistent with research indicating parallel and independent development of implicit and explicit knowledge in the serial reaction time task (Willingham et al., 1989). Interactions between explicit and implicit learning are explored in more detail in the final section; with regard to response modalities, it is sufficient to note that explicit knowledge can be considered to be another form of knowledge accessed by another response modality, namely verbal report.

Attentional and Working Memory Requirements of Implicit Learning

Several researchers have argued that implicit learning requires attention (Carlson & Dulany, 1985; Nissen & Bullemer, 1987). However, there are several separate meanings of the term attention that are relevant to implicit learning. First, attention refers to whether the stimulus is consciously perceived; in some situations, such as subliminal presentation, stimuli are not fully consciously perceived. Can implicit learning occur at all under these conditions, and, if so, how well? Second, there is the question of whether minimal attention is sufficient for optimal implicit learning or whether additional processing helps learning. How automatic is implicit learning, and to what degree is learning influenced by strategies used by the learner? Third, attention refers to a set of orienting and focusing systems. Which of these systems are necessary for implicit learning? Fourth, attention refers to the limited capacity that humans have for performing conflicting cognitive processes simultaneously (e.g., different working memory processes). Which of these working memory processes are necessary for implicit learning, and how is implicit learning affected when it occurs under dual task conditions that interfere with one or more of these processes?

Minimum Amounts of Attention Required for Implicit Learning

Several studies have investigated whether subjects can learn anything about material presented in ways that do not allow for large amounts of cognitive processing. This includes material presented subliminally, as irrelevant or unattended but superimposed stimuli or features in visual concept experiments and to the unattended ear in dichotic listening. In these situations, subjects are not conscious of the stimulus (in subliminal presentation and dichotic listening) or the stimulus is present only in iconic memory and does not receive further processing (in visual attention experiments and the Sperling partial report procedure). As shown in Table 4, there has been little research investigating implicit learning under minimally attended conditions. However, research has been performed on related tasks,

<table>
<thead>
<tr>
<th>Task</th>
<th>Attentional manipulation</th>
<th>Unattended superliminal visual</th>
<th>Dichotic listening</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artificial grammar</td>
<td>Subliminal</td>
<td></td>
<td>No</td>
</tr>
<tr>
<td>Visuospatial concepts</td>
<td></td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Covariation learning</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Serial reaction time</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Contingent response</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hebb digits</td>
<td></td>
<td></td>
<td>No</td>
</tr>
<tr>
<td>Puzzle learning*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Motor learning</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Function matching</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dynamic systems*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Related task</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mere exposure effect</td>
<td></td>
<td>Yes (polygons)</td>
<td>Yes (tone pattern)</td>
</tr>
</tbody>
</table>

* Not possible to present relevant stimuli under minimal attention without drastically changing the nature of the task (included for reasons of completeness).
and together they indicate some provocative possibilities that require further studies for confirmation.

There is evidence that subjects retain memory traces of material presented subliminally that are accessible to conceptual fluency judgments. Kunst-Wilson and Zajonc (1980) found that subjects subliminally presented with polygons showed greater liking for the subliminally presented items than for novel items, although conscious recognition of the items was at chance. Later research showed that the effect was undiminished after 1 week (Seamon, Brody, & Kauff, 1983). Although Kunst-Wilson and Zajonc argued that the subliminal mere exposure effect is a specifically affective process, later research has demonstrated that the information gained in subliminal presentations is accessible to other conceptual fluency judgments: Bonanno and Stillings (1986) showed that familiarity judgments of stimuli were equivalent to affective judgments, and G. Mandler et al. (1987) showed that subjects were able to make brightness discriminations at a level similar to affective judgments (the types of judgments that can be made on the basis of conceptual fluency were discussed earlier). Subjects are able to differentiate learned polygons from unlearned polygons that differ only in lengths of lines, implying that a certain degree of representational complexity is involved in subliminal mere exposure; however, whether subjects can generalize their knowledge to novel stimuli has not been tested, and, aside from the similarity in response modality, it is unclear the extent to which the knowledge gained is otherwise comparable to implicit learning of visual concepts.

Is it possible to show implicit learning for visual items in superliminal but minimally attended situations? Musen and Squire (1993) found that subjects demonstrate learning of covariations between word identity and ink color in a Stroop task; subjects are able to name the ink color more quickly over trials when ink color and word identity are covaried, and this learning is disrupted when the relationships are changed. However, subjects do not show disruption of learning when an irrelevant dimension (the typeface of the word) is changed. This experiment implies that implicit learning may only take place when the relevant stimulus features are attended to and actively processed. However, J. Miller (1987), in a study in which subjects responded to the central letter in a visual display, found that subjects are sensitive to covariations between the unattended flanker letters and the attended central stimulus. Carlson and Dulaney (1985) found no concept learning when concept exemplars were presented in uncued lines in a Sperling partial report procedure. However, their methodology was not conducive to implicit learning: Subjects were not told which exemplars were in which category until after learning was complete, and the features of the concept (letters) had no positional dependencies within the strings. These results together indicate that attentive processing is usually required for learning but that it may not be necessary in some cases (e.g., learning simple covariations when other covariations are not present).

Kahneman and Treisman (1984) argued that unattended stimuli in dichotic listening are not processed without attention, except for occasional intrusions. Evidence from implicit learning studies is inconclusive: Wilson (1979) showed a mere exposure effect for tone patterns presented to the unattended ear of a subject shadowing verbal stimuli, but Kidd and Greenwald (1988) found no Hebb effect from 10 consecutive repetitions of a digit sequence to the unattended ear. It is unclear how to interpret these results; the mere exposure effect in Wilson's study could be an artifact of the fact that the experiment mixed tones and verbal stimuli that may be processible in parallel. Alternatively, Kidd and Greenwald's results could be due to peculiarities of the Hebb digits task (discussed in more detail in the section concerning the role of the hippocampus in implicit learning) rather than characteristic of implicit learning in general; further research is needed to determine how well most forms of implicit learning are learned in dichotic listening conditions.

In conclusion, it appears that some forms of implicit learning may occur under conditions of limited attention, such as mere exposure effects from stimuli presented subliminally or as unattended stimuli in dichotic listening or covariations between ignored and attended stimuli. However, not all implicit learning processes can work at top efficiency, as shown by the lack of the Hebb digits effect in the unattended ear in dichotic listening and the lack of concept learning in uncued lines in the Sperling partial report task. It is not yet clear how much attention processing is required by each implicit learning task. Some implicit learning may occur with very little attention, but other forms of implicit learning that require attention to particular details (e.g., the Hebb digits effect, in which a particular order of the elements must be learned, despite distractors) may require relatively large amounts of processing. Alternatively, perhaps visual concepts are learned (perhaps through the mediation of the visuospatial sketch pad, discussed in more detail in a later section) but functional or predictive relations are not. Or subjects may learn some sorts of relations subliminally but not others, perhaps reflecting some of the biases outlined earlier. For example, Greenwald (1992) suggested that covariations among physical features of unattended objects might be learned subliminally but that more abstract covariations may require attention.

**Automaticity of Implicit Learning**

The research discussed here implies that implicit learning of relatively complex stimuli may require a certain minimal amount of attention. Is this minimal amount of attention enough, however, for optimal learning? Or will additional cognitive processing lead to better learning? In other words, to what degree is implicit learning an automatic process? Hasher and Zacks (1979; Zacks et al., 1982) suggested that frequency monitoring, which may be related to implicit learning, is automatic and does not require more than minimal attention. They claimed that automaticity implies five characteristics in a system: It must take minimal resources from limited-capacity attentional systems, must not interfere with other cognitive processes, must not benefit from practice, must function consistently regardless of subjects' state, and must occur without intention to learn. Implicit learning meets the last two criteria: It is incidental and appears to function regardless of subjects' psychological state (Abrams & Reber, 1988). However, it does not meet the first three criteria. It requires attention and hence interferes with other cognitive processes, as shown in dual task research (A. Cohen et al., 1990; Dienes et al., 1991; Nissen & Bullemer, 1987); in addition, subjects benefit from practice in
sequence learning tasks (Lewicki et al., 1987). Since Hasher and Zacks's (1979) study, other researchers have shown that frequency learning itself does not meet the first three criteria. Subjects' learning is influenced by the amount of practice they have with the stimuli and the particular orienting task performed on the stimuli (Fisk & Schneider, 1984; Sanders et al., 1987). Sanders et al. (1987) suggested that the idea of automaticity be modified to allow learning to benefit from particular forms of cognitive processing in different orienting tasks and from practice. They argued that the crucial aspects of automaticity are that some if not complete learning takes place when stimuli are minimally attended and that learning occurs incidentally. Implicit learning meets this modified view of automaticity.

This view of automaticity leaves open the possibility that implicit learning can be influenced by processing that is consciously controlled by the subject. Subjects can choose to process stimuli in ways that allow implicit learning to function more effectively. For example, a subject in an artificial grammar learning task could choose to put effort into learning the grammar strings. This subject may well be able to perform grammaticality judgments better than a subject who paid little attention to the strings in the learning phase. However, this does not mean that subjects can directly aid the implicit learning process by conscious hypothesis testing; as shown by A. S. Reber (1976; Reber, Kassin, Lewis, & Cantor, 1980), subjects who are instructed to explicitly look for rules during the learning phase perform worse on grammaticality judgments than subjects instructed to merely memorize the strings. A recent study by LeCompte (1992) shows one way that subjects can have (in LeCompte's words) willful control over the grammar learning process. LeCompte had subjects study strings with irrelevant letters inserted into them. Subjects who were told which letters were irrelevant performed better than subjects who were not informed about the irrelevant letters, indicating that the former subjects were able to consciously disregard those letters, which helped their implicit learning. However, these subjects performed at a lower level than subjects given the strings without the irrelevant letters, indicating that simply ignoring the letters was insufficient to eliminate their deleterious effect on implicit learning. In conclusion, implicit learning can be affected by the type of cognitive processes performed on the stimuli presented, and some of these processes can be influenced by conscious strategies on the part of the subject, although not by conscious hypothesis-testing forms of explicit thought. The next two sections examine the attentional and working memory processes that may be involved in implicit learning and what kinds of learning they produce.

Role of Attentional Systems in Implicit Learning

Attention is often characterized as a process that focuses cognitive resources on particular objects or spatial locations. Bullemer and Nissen (1990) argued that attentional orienting processes are involved in learning the serial reaction time task. They found that subjects trained on a pattern are slower to respond to an incorrect stimulus than control subjects responding to completely random stimuli. They argued that this result implies that these subjects have already oriented their attention to the expected stimulus location, and cost is incurred when they must disengage from that location and shift to the unexpected one. Although Bullemer and Nissen's (1990) findings are consistent with their explanation in terms of attentional orienting, the findings are also consistent with an interpretation in terms of response selection. Earlier stimuli could prime a particular button pressing response, so that when an incorrect stimulus is shown there is cost in shifting from the primed response to the new response. Other studies are consistent with response programming playing an important role in the serial reaction time task. Huntington's disease and Parkinson's disease patients, both of whom are subject primarily to motor response programming deficits, are impaired in the serial reaction time task (Ferraro et al., 1993; Knopman & Nissen, 1991). Willingham et al. (1989) performed an experiment in which they isolated the spatial component of the responses from the spatial component of the stimuli by having subjects respond to the color of the stimulus rather than its location. They found that subjects who were led to make a spatially patterned series of responses but who did not view spatially patterned stimuli showed learning, but subjects given a spatial pattern in the stimuli without a pattern in the responses did not. Presumably, if learning occurs primarily in terms of attentional orienting in serial reaction time, subjects should show the opposite pattern of learning: They should learn when the stimuli are spatially patterned but not when only the responses are. In conclusion, although Bullemer and Nissen's (1990) findings are suggestive, they do not, in themselves, constitute sufficient evidence that implicit learning necessarily involves visual attention orienting.

Posner and his colleagues (Posner & Petersen, 1990; Posner & Rothbart, 1992) have argued that attention in the sense of orientation consists of three neurologically and functionally separable systems: the posterior system, which carries out functions focusing attention on a particular location and need not be conscious; the anterior system, which is involved in detecting events and ordering the shifting of the focus of attention and is conscious; and the vigilance system, which works on both posterior and anterior systems to produce an alert state of readiness. Posner and Rothbart (1992) contended that Bullemer and Nissen's results indicate that the serial reaction time task involves subjects' learning a program for the posterior attention system consisting of a series of locations. Because the posterior system need not be conscious, this explanation is consistent with the serial reaction time task not involving awareness of the pattern learned on the part of the subject. In addition, the authors interpreted the A. Cohen et al. (1990) study (discussed in more detail later), which showed learning in dual task situations of unique and hybrid sequences (all unique pairwise relationships or at least one unique pairwise relationship, respectively) but not of ambiguous sequences (no unique pairwise relationships), as indicating that there are limits on what is computable without conscious attention by the posterior system alone. Hence, they suggested that, in ambiguous sequences, the anterior system is involved in learning what is ultimately a posterior attention system program but that the posterior system alone can learn unique and hybrid sequences.

In sum, attentional orienting programs may play an important role in learning serial reaction time and similar tasks, although the experimental evidence so far is inconclusive. It is also unclear to what degree other implicit learning tasks might
depend on these attentional mechanisms. Simple orienting to the stimuli appears to play a role only in spatially structured sequence learning tasks. Visual concept learning and function learning are unlikely to involve orienting as a key element because of the use of single stimuli and the lack of time pressure in making responses; the stimuli are fully perceived and processed before decisions are made, and any differences in orienting should not be an important part of learning.

Role of Working Memory Systems in Implicit Learning

Several researchers have examined the effects of attentional division on implicit learning through dual task paradigms. Although some have treated attention as if it were a single capacity needed by both implicit learning and the dual task (Nissen & Bullemer, 1987), this view has been criticized recently, and most modern theorists prefer to interpret dual task interference as interference among multiple attentional and other cognitive processes (Allport, 1989; Navon, 1985; Neumann, 1987). This section explores how dual task paradigms can illuminate the dependence of implicit learning on different working memory systems, specifically interpreted within the framework of Baddeley’s (1992) theory of working memory. It should be noted that the discussion involves the effects of the dual tasks on the learning of implicit knowledge rather than the expression of already-learned implicit knowledge. A few studies have investigated the effects of an added dual task on the expression of knowledge already acquired in single task conditions; the results of these studies are summarized in Table 5. Pew (1974) found that the dual task interfered with subjects’ implicit knowledge of a repeated portion of a sequence in a motor tracking experiment. Curran and Keele (1993) found that adding a dual task interfered greatly with subjects’ knowledge of ambiguous structures, which they claimed rely on a hierarchical mechanism, but did not strongly interfere with knowledge of hybrid structures (sequences with at least one unique pairwise relationship). Hayes and Broadbent (1988) found that adding a dual task did not affect subjects’ ability to control a dynamic system. In conclusion, adding a dual task appears to affect expression of hierarchical learning and complex motor pattern learning while not interfering with the expression of linear association knowledge or dynamic systems knowledge, implying that different types of implicit knowledge are affected differently by the imposition of the dual task; stronger conclusions await further research.

The effects of dual tasks on implicit learning have been studied in serial reaction time (A. Cohen et al., 1990; Keele & Jennings, 1992; McDowall, Lustig, & Parkin, 1993; Nissen & Bullemer, 1987), artificial grammar learning (Dienes et al., 1991), puzzle learning (P. J. Reber & Kotovsky, 1992), and dynamic systems learning (Hayes & Broadbent, 1988; see Table 5 for a summary). The serial reaction time studies used a tone counting task in which subjects hear one of two possible tones after each response and count the total number of one of the types presented. Subjects in the artificial grammar and dynamic systems studies, and a subset of subjects in the puzzle learning studies, used the random digit (or letter) generation task, in which they had to generate a digit on each trial, being careful not to state the digits in any pattern. Another group of puzzle learning subjects was presented with a series of letters, one every 3 s, and had to remember the last one, two, or three of them; they were periodically interrupted and asked to recall. In the serial reaction time studies, the tones appeared in the interstimulus interval between lights; in the artificial grammar and dynamic system studies, subjects were cued to generate a digit at intervals approximately 2 s apart, which in practice meant between moves in the dynamic systems task, and during the 5-s memorization period in the grammar task. The dual task was present throughout the task in serial reaction time and during learning and transfer in the dynamic systems task; however, it was present only during study of the strings in the artificial grammar task.

A. Cohen et al. (1990) found that the dual task, regardless of

<table>
<thead>
<tr>
<th>Implicit task</th>
<th>Dual task</th>
<th>Effect on learning</th>
<th>Effect on expression</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artificial grammar</td>
<td>RNG</td>
<td>Interfered; positional</td>
<td></td>
</tr>
<tr>
<td>concepts</td>
<td></td>
<td>dependencies eliminated</td>
<td></td>
</tr>
<tr>
<td>Covariation learning</td>
<td>Tone counting</td>
<td>Eliminated: ambiguous</td>
<td></td>
</tr>
<tr>
<td>Serial reaction time</td>
<td></td>
<td>Interfered: hybrid, unique</td>
<td></td>
</tr>
<tr>
<td>Contingent response</td>
<td>Memory load</td>
<td>None: final performance</td>
<td></td>
</tr>
<tr>
<td>Hebb digits</td>
<td></td>
<td>Interfered: initial learning</td>
<td></td>
</tr>
<tr>
<td>Puzzle learning</td>
<td>Memory load</td>
<td>Eliminated learning</td>
<td></td>
</tr>
<tr>
<td>Motor learning</td>
<td>RNG</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Function matching</td>
<td></td>
<td>Interfered</td>
<td></td>
</tr>
<tr>
<td>Dynamic systems</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. RNG = random number generation.

Table 5
Effects of Dual Tasks on Implicit Learning
its level of difficulty, affected serial reaction time by preventing
the learning of ambiguous sequences (no unique pairwise
relations) but not the learning of unique or hybrid sequences (only
or at least one unique pairwise relation, respectively). Nissen
and Bullemer (1987) also found that the dual task prevented
learning of their sequence, which is ambiguous according to the
definition of Cohen et al., when measured by reaction time de-
crease over trials. McDowall et al. (1993), however, found learn-
ing of the same sequence when the measure of learning was the
difference in reaction time between the previous pattern block
and a final random block. Their results may be resolved with
Cohen et al.'s findings by considering the differences between
the sequences used: Although Nissen and Bullemer's sequence
is ambiguous in the sense that there are no unique pairwise re-
lations between locations, the pairs do vary in their frequency
of occurrence, whereas the pairs appear with the same fre-
cuency in the Cohen et al. sequence. Keele and Jennings (1992)
also showed some learning of ambiguous sequences in dual task
conditions, using sequences that were more similar to the Co-
en et al. sequences; it is unclear what can account for the
difference between their results and Cohen et al.'s. In general,
learning of ambiguous sequences in dual task conditions might
be due to subjects being partially aware of the sequence; Carran
and Keele (1993) showed that low-awareness subjects did not
evidence any knowledge of an ambiguous sequence that they
learned under single task conditions when they were switched to
a dual task.

The dual task interfered with grammar learning and elimi-
nated subjects' knowledge of positional dependencies, regard-
less of what priority subjects were told to give each task. Initial
puzzle learning was slowed by the memory task, but subsequent
performance on the puzzle was independent of memory load;
subjects who were performing random-digit generation showed
very poor initial performance, but their performance on a sec-
ond try was not evaluated. Learning of implicit dynamic sys-
tems and transfer to related systems were unimpared by the
dual task.

Some interesting relationships are visible in the pattern of
data even without taking into account the differences in sec-
ondary task. It is interesting that both ambiguous sequence learning
in serial reaction time was lost and positional dependencies in
artificial grammar learning were eliminated. These effects indi-
cate that the dual task may interfere with hierarchical process-
ing (A. Cohen et al., 1990) in both tasks. It is also interesting
that each of these areas showed some interference from the dual
tasks, except for implicit dynamic systems learning, which was
not affected. Because dynamic systems learning is no simpler
than other implicit learning tasks, the effect of a dual task is not
merely a function of its overall difficulty but probably depends
on factors such as the stimulus structure and the response mo-
dality involved. The results of the puzzle and artificial grammar
studies, in which there was a dual task during initial learning
but not final performance, indicate that learning may occur
during dual tasks but not be visible until the dual task is re-
oved. Experiments that varied the difficulty of the dual task
found that subjects performed equivalently regardless of the
level of difficulty. These results imply that whatever resources
are affected by the dual task are affected in an all-or-none man-
ner.

Additional insights from the dual task experiments can be
obtained by analyzing specific cognitive processes interfered
with by such tasks. Baddeley's (1992) theory of working mem-
ory forms a conceptual framework for this speculative analysis.
In Baddeley's theory, there are three components to working
memory: a central executive system and two slave systems, the
articulatory loop and the visuospatial sketch pad. The central
executive is, by Baddeley's admission, an area of residual igno-
rance; it includes functions such as coordinating the slave sys-
tems, interacting with long-term memory, and engaging, shift-
ing, and reengaging attention. Baddeley has claimed that ran-
dom digit generation is an ideal task for interfering with the
central executive and interfering only minimally with the other
two systems. The articulatory loop holds a limited amount of
verbal material, represented phonologically; it is the system in-
volved in such common tasks as rote repetition of a list or phone
number. It is blocked effectively by requiring the subject to re-
peat an irrelevant sound incessantly. The visuospatial sketch
pad holds short-term visual images and spatial information; it
is interfered with by a spatial key-tapping task.

Except for the random number generation, none of the dual
tasks used in implicit learning research clearly map onto Bad-
deley's tasks. However, it is reasonable to suppose that the tone
counting tasks and letter memory tasks both involve the articu-
latory loop, in that the total tone count and letters must be re-
hearsed to be maintained. In addition, they both require some
central executive function in disengaging, shifting attention,
calculating the new tone count, or recognizing the new letter
and dropping the oldest of the remaining letters. Even random
number generation in the circumstances of these studies may
have included some articulatory loop function if subjects had
repeated to themselves the last few digits generated to make sure
that their next selection was random.

One conclusion is that, apparently, the central executive may
be necessary for full grammar learning and initial puzzle solv-
ing. The latter is not surprising; many conscious hypothesis-
testing sorts of explicit thinking are necessary for puzzle solv-
ing, and they presumably are related to the central executive.
The former is consistent with the central executive being re-
quired for learning hierarchical relations, as shown in positional
dependencies and serial reaction time learning of ambiguous
sequences.

As for the articulatory loop, the results that have been pro-
duced indicate that it could be involved in induction of hierar-
chical relations. Subjects learning artificial grammars show no
knowledge of positional dependencies of bigrams within strings
after study with a random number generation dual task, which
is consistent with such a role for the articulatory loop (Dienes et
al., 1991), although the random number task is confounded
with the central executive. Likewise, serial reaction time learn-
ing of ambiguous sequences could have articulatory loop ele-
ments. Finally, the Hebb digits task may be carried out to a large
part by processes local to the articulatory loop, as indicated by
the lack of learning of amnesic subjects for sequences larger
than their digit span. The role of articulatory loop may be to
hold the elements in the proper order so that other cognitive
processes can act on them; the articulatory loop itself need not
carry out the abstraction. At this point, it is only possible to
speculate on the role that the visuospatial sketch pad may play.
However, it might be important in inducing spatial information (e.g., absolute spatial dependencies) and any particularly visual features (e.g., color).

Because so much implicit learning research involves motor learning and motor responses, it is of interest whether there is a specifically motor short-term memory module or slave system analogous to the articulatory loop. Research indicates the presence of motor short-term memory (Adams & Dijkstra, 1966; Wilberg & Salmela, 1973), and interference studies show that coding within this type of memory involves visuospatial as well as kinesthetic codes (Diewert, 1975). Simple motor activity without concomitant memory load regarding position or other information does not appear to interfere with motor skill learning (Shea & Upton, 1976); therefore, motor short-term memory may have properties in common with the visuospatial sketch pad (especially because the interfering task for the visuospatial sketch pad, patterned key tapping, contains motor elements). It is not clear whether motor short-term memory is a separate module like the articulatory loop or a combination of the visuospatial sketch pad and motor elements, and it is certainly not clear what role this module, should it exist, may play in implicit learning.

It should be kept in mind that complex structures, such as artificial grammars, may be learned through the interaction of many processing systems. Interference with one or more of these systems might not completely eliminate learning but, more interestingly, eliminate one component of learning from the overall pattern. For example, it is possible that if one interfered with the visuospatial sketch pad, subjects would no longer show knowledge of absolute spatial dependencies but still would show knowledge of relative positional dependencies, which may be subserved by central executive function.

Representation of Implicit Knowledge

This section outlines what is known about the mental representations that underlie implicit knowledge and argues that subjects learn abstract, although probably instantiated, representations rather than aggregate or verbatim representations. The first important question about the representation of implicit knowledge is whether it is instantiated; that is, is it independent of physical form and sensory modality of stimuli or linked to these surface features? Theorists who propose that representations are not instantiated usually claim that they consist of sets of abstract rules or patterns. Three possible representational structures have been postulated for instantiated representations. The first is that representations are in the form of abstract rules but are linked to surface features. The second and third, called aggregate and verbatim theories by Stadler (1992), postulate that implicit knowledge consists of representations of exemplars. In verbatim representations, whole stimuli are stored; in aggregate representations, partial stimuli are stored. In both cases, novel stimuli are evaluated through a process of comparison or analogy to the previously stored stimuli. This section begins with a discussion of what kinds of transfer between stimuli are possible within implicit learning and then evaluates these representational theories in that context.

Determining what representations subjects learn is a difficult problem because subjects may be sensitive to many different pieces of information. Showing that subjects are sensitive to bigram information in artificial grammars, for example, does not rule out that they are also sensitive to trigram information or positional dependencies of individual letters. In dot pattern learning, subjects are sensitive to relations between subgroups of dots, not only to the relations of individual dots to the prototype (Hock, Tromley, & Polman, 1988). In principle, it is difficult to distinguish these theories empirically because they lead to structure–process trade-offs. Any evidence that subjects can transfer to stimuli with different instantiations can be explained by adding comparison processes that map an instantiated representation onto a different instantiation. Evidence that subjects are sensitive to another invariant of the learned stimuli can be explained by adding another feature to the mechanism that compares novel stimuli with the representation or representations of old stimuli. However, as discussed in the introduction, the preservation of implicit learning in cases of amnesia indicates that it is based on nonhippocampal memory systems, and, therefore, any theory that postulates that the mental representation of implicit knowledge is based on explicit memories (e.g., the theory presented by Mathews et al., 1989, and Druhan & Mathews, 1989) is in doubt.

If the representations are instantiated and particularly aggregate or verbatim, they must be so within a nonhippocampal system.

Table 6
Transfer to Novel Stimuli

<table>
<thead>
<tr>
<th>Task</th>
<th>Same surface and deep structure</th>
<th>Different surface, same deep structure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artificial grammar</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Visuospatial concepts</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Covariation learning</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Serial reaction time</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Contingent response</td>
<td>Yes</td>
<td>Mixed</td>
</tr>
<tr>
<td>Hebb digits</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Puzzle learning</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Motor learning</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Function matching</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Dynamic systems</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

Transfer of Implicit Knowledge to Novel Stimuli

Before exploring this controversy more fully, it is important to determine the degree to which implicit knowledge transfers to related stimuli (note that this is different from the transfer between response modalities, in which the stimuli are the same but the response modality is changed), because accounting for transfer provides important constraints for theories. There are two kinds of transfer: transfer to items that share surface structure (or instantiation), as well as the same deep structure, and transfer to items that share only deep structure with different surface structures. These transfer results are summarized in Table 6. Most studies show good transfer to related stimuli that share surface structure. In visuospatial concepts and artificial
grammars every study indicates that subjects are able to classify novel patterns. In covariation learning, subjects apply the covariation they have learned to novel stimuli. In function matching learning, subjects are able to transfer their learning of one portion of the function to other portions (Koh & Meyer, 1991), and, in dynamic systems, subjects learn to control systems that have such large state spaces that it is unlikely that the subjects have repeated experience with identical situations. In addition, subjects show good transfer to systems with similar cover stories and identical underlying functions (Berry & Broadbent, 1988). In sequence learning, however, subjects are usually learning invariant sequences or a limited number of relationships, so it is unclear how much transfer to related sequences may occur. However, Pew (1974) showed some transfer to an inverted pattern in his tracking experiments, and Schwartz and Bryden (1971) found that changing two digits within the string (as long as they were not the initial two) did not eliminate the Hebb digits effect. In addition, Stadler (1992) found that subjects trained on serial reaction time sequences with higher levels of statistical structure (longer runs repeated more often) learned better than subjects trained on sequences with lower levels of structure. This result implies that learning of one part of the sequence can influence learning of the other parts.

Transfer to stimuli with different surface structures but the same deep structure has been performed in artificial grammars. A. S. Reber (1967) found perfect transfer to strings based on the same grammar but involving a different letter set when subjects were evaluated in terms of time to criterion for memorizing the strings. Mathews et al. (1989), however, showed some transfer but nevertheless degraded performance when subjects were asked to make grammaticality judgments about strings with different letter sets. Manza and Reber (1992) found transfer between grammar strings presented auditorily and tested visually, and vice versa. In addition, they found transfer between light sequences and tone sequences, in which the light stimuli were distinguished by spatial location and the tone stimuli by pitch, when the sequences were based on the same artificial grammar. However, other areas of implicit learning have revealed no ability to transfer between related structures. In dynamic systems research, subjects were unable to transfer to a system with identical underlying equations but a different cover story (Berry & Broadbent, 1988). In the contingent reaction time task, evidence for transfer is mixed. Stadler (1989) found that minor changes in perceptual properties of the stimuli greatly interfered with expression of learning, even though the underlying rules were unaffected. However, Lewicki, Hill, & Czyzewska (1992) found that subjects could transfer knowledge between different but structurally similar matrix patterns when learning was measured as savings in learning the second pattern. Similarly, Kush- ner et al. (1991) found that when mapping between the rules and the locations was changed, subjects’ learning was impaired, although they eventually relearned the task.

Abstract Versus Instantiated Theories

The controversy over the form of representation of implicit knowledge was originally phrased as whether subjects develop abstract knowledge in implicit learning (A. S. Reber, 1989). There are two ways in which representations can be abstract: The rules learned can be at a deep level and independent of surface features of the stimuli, or they can be rules that are instantiated and use surface features as variables. A. S. Reber (1969) originally considered implicit knowledge to be abstract in the first sense (general rules with variables that can be filled with many actual features; i.e., a legal string may include an element followed by two of a different element); however, he later extended his definition to include instantiated knowledge of permissible letter bigrams (A. S. Reber, Allen, & Regan, 1985). Some of the transfer research discussed in the previous section indicates that subjects may be learning abstract rules about stimuli independent of the surface structure or instantiation. However, the evidence is strongest in the area of artificial grammars. At this point, it is not possible to definitively conclude whether subjects learn abstract rules or perform their grammaticality judgments on items with different surface structures through a combination of explicit analogy and instantiated implicit knowledge of patterns. It should be noted that there is no reason to expect that learning cannot consist of a combination of instantiation-linked rules together with non-instantiated abstract rules. In addition, the relative importance of abstract and instantiated representations may differ in different implicit learning tasks and response modalities.

Instantiated Theories: Abstract, Aggregate, and Verbatim

This section asks whether instantiated representations based on verbatim or aggregate storage of stimuli can be adequate accounts of implicit knowledge. Verbatim theories argue that whole exemplars are stored, and aggregate theories argue that fragments are stored. The former idea has been championed most vigorously by Brooks (1978). Brooks used a paired associates methodology in which subjects memorized paired associates of grammar strings with words (that were animal or city names) and then were told that the pairs were representative of two concepts (old world and new world items). Subjects therefore had to perform abstraction after learning, and Brooks (1978) argued that the only way they could have done so is through analogy to stored exemplars. A. S. Reber and Allen (1978) countered that the paired associates procedure led to qualitatively different learning than observational learning alone, or to the traditional memorization to criterion learning method, and that Brooks was measuring not true implicit learning but a different process.

Vokey and Brooks (1992; Brooks & Vokey, 1991) and McAn- drews and Moscovitch (1985) used a method wherein they pit- ted the similarity of test strings to the learning set against the grammaticality of the strings. They found that subjects classified novel strings based on both factors. Fried and Holyoak (1984) found that subjects classify novel exemplars of visuospatial concepts into the concepts in which they are most likely to be included, taking into account the variance of the categories, not just by similarity to stimuli in the learning set. Homa, Ster- ling, and Trepel (1981) found that subjects rate the typicality of the prototype higher than similarity to learned exemplars alone would lead them and that test delay reduces the role of simi- larity in judgments. A. S. Reber and Lewis (1977) found that, in an anagram task, subjects would use bigrams in frequencies
closer to what they were in the grammar as a whole rather than
in proportion to the frequency with which they appeared in the
study strings. In sum, although subjects appear sensitive to the
similarity of the test exemplars to the exemplars in the learning
set, they do not make their judgments solely on the basis of sim-
ilarity.

The evidence just summarized does not provide a convincing
case that implicit learning of visual stimuli occurs through a
process of analogy to stored whole exemplars and, therefore,
sheds doubt on verbatim theories. Rather, the research indicates
that the degree of adherence to abstracted commonalities of
items is a strong determinant of subjects’ judgments. It is im-
portant to realize that the type of abstraction found may depend
on the time of abstraction. The implicit learning tasks consid-
ered here all involve extracting patterns as stimuli are studied.
However, it is possible to present stimuli in such a way that
abstraction is not possible until after the stimuli are learned. As
mentioned earlier, this type of presentation may have been in-
volved in Brooks’s (1978) paired associates work. Subjects may
well perform post hoc abstraction through a process of compar-
ision with stored exemplars, which may lead them to use differ-
ent kinds of stimulus information in their abstractions. For ex-
ample, Medin et al. (1983) had subjects study pictures of faces
and names. Some subjects were told which family each face was
from while they were studying, and others only learned af-
fterward. The latter group showed lower reliance on imperma-
nent features of the faces (e.g., smiles and hair length) than the
former group.

Other researchers have proposed that subjects are learning an
aggregate representation consisting of many fragments of stim-
uli, rather than whole stimuli, and that novel stimuli are classi-
fied on the basis of how well they match these fragments. Du-
lany et al. (1984) had subjects mark which portions of artificial
grammar strings were responsible for making them grammatic-
al or not. They took the portions marked to be a rule that sub-
jects held about the grammar and found that these rules ac-
counted for subjects’ performance without significant residual.
In a similar study, Perruchet and Pacteau (1990) compared sub-
jects who studied only the letter bigrams from a set of strings
with subjects who studied the strings themselves and found that
the two groups performed similarly on a well formedness task.
They also argued that subjects’ ratings of bigrams as familiar
or nonfamiliar could be used to account for their classification
of strings, but their study and simulation had several methodolog-
ical problems (Mathews, 1990; A. S. Reber, 1990); thus, it is
unclear how conclusive their results are. Perruchet, Gallego,
and Pacteau (1992) had subjects who studied only bigrams
complete anagrams as in A. S. Reber and Lewis (1977). Subjects
who studied whole strings did better overall than the bigram
and showed more of a grammaticality effect, but both
groups used bigrams in their anagrams more in proportion to
how often they appeared in the grammar as a whole than how
often they appeared in the study strings; it is unclear how more
knowledge of bigrams could lead to this result. In sum, bigram
knowledge can account for a large amount of the information
subjects learn about strings. However, there are other aspects
that a strict bigram theory cannot explain, such as the sensitiv-
ity of subjects to the positional dependencies of bigrams within

Biases and Dissociations in Implicit Learning

Two important approaches to exploring the structure of im-
licit learning mechanisms are to find areas in which subjects
show biases toward learning particular relations and to find dis-
associations between what subjects find easy to learn and what
they find difficult or impossible. These biases and dissociations
in the implicit learning system provide important constraints
for possible theories of implicit learning. Three types of biases
are shown in the implicit learning literature: biases toward in-
ducing particular forms of information, biases toward learning
systems with correlated factors, and biases toward spatially and
temporally organized information. In addition, a dissociation
between learning pairwise associations and hierarchical rela-
tions indicates that there may be separate mechanisms for
learning each.

Biases Toward Particular Forms of Information

Subjects show biases toward inducing certain concept forms
and certain function forms, which indicates that implicit learn-
ing mechanisms may be structured in a way that they easily
induce some patterns but induce others with difficulty. Flannan-
gan, Fried, and Holyoak (1986) showed that subjects are biased
toward inducing concepts that follow a normal distribution
rather than concepts with a U-shaped distribution. This bias is
influenced by past experience, in that subjects with experience
studying a concept with a nonnormal distribution are able to
learn a concept with a novel nonnormal distribution better than
subjects with experience in learning normal concepts only.

Several studies show that subjects in function matching ex-
periments are biased toward inducing linear functions rather
than sine functions, although they are able to induce sine func-
tions given sufficient training (Deane et al., 1972; Hammond &
(1991) compared linear functions with other monotonic
functions and found that subjects showed a systematic bias to-
ward inducing a power function when learning a functional re-
lationship between a line length and a time interval. Because
power functions are linear in log–log coordinates, the authors
argued that this bias is consistent with logarithmic transforma-
tions of sensory input in psychophysical systems. Price et al. 
(1992) extended the work of Koh and Meyer in a study of 
induction of a function of two variables. They presented subjects 
with inclined planes that varied in length and degree of inclination 
and asked them to predict how long it would take for a ball to 
roll down the plane. They found that subjects showed a cor-
rect bias for the relationship between length and time and 
learned it easily; however, they showed an incorrect bias for the 
relationship between duration and angle and learned it more 
slowly.

Correlated Features Bias

Subjects may have a bias toward learning and processing fea-
tures that are involved in a common system of relations. The 
degree to which features are correlated is known as the system-
aticity of a system. Billman (1989) found that learning of rules 
was facilitated by the presence of other intercorrelated rules in 
an artificial language learning task; at least some of her subjects 
learned without explicit knowledge of the rules induced, indi-
cating that her task may have implicit elements. Kersten and 
Billman (1992) found that subjects who were asked to observe 
events presented on a computer and then asked to rate novel 
 displays for how good an example they were of possible events 
performed better in situations in which possible events were 
correlated. The use of ratings as the dependent measure indi-
cates that subjects may have used their conceptual fluency as 
the basis of their responses and may have learned implicitly, al-
though the authors did not mention the degree of explicit 
knowledge their subjects acquired. On the basis of these studies, 
it seems reasonable to propose that implicit learning processes 
are probably biased toward learning about structures that have 
a high level of systematicity. Stadler’s (1992) research, in which 
he varied the statistical structure of sequences and found better 
learning of sequences with a high level of statistical structure, 
also supports the idea that implicit learning is biased toward 
learning correlated features. Sequences with higher levels of sta-
tistical structure have longer, more frequent runs and, hence, 
a higher correlation between parts of the sequence. Similarly, 
Elman (1990) pointed out that increasing the number of se-
quential dependencies need not lead to worse performance in 
sequence learning because the more complicated sequence can 
be redundant.

Spatial and Temporal Biases

There are strong a priori reasons to propose that spatial and 
temporal factors should important to implicit learning. Studies 
of animal cognition emphasize the importance of spa-
tial and temporal factors to animals (Gallistel, 1990). If implicit 
learning is an evolutionarily early process (A. S. Reber, 1992), it 
would be reasonable to assume that spatial and temporal factors 
play a special role in such learning not shared by other features, 
such as color. Several lines of research confirm the importance 
of spatial factors in implicit learning. In serial reaction time and 
contingent response tasks, spatial alterations have devastating 
effects on performance (Stadler, 1989), and spatial factors make 
it easier to learn a serial reaction time task with verbal compo-
nents (Hartman et al., 1989). Dynamic systems are much easier 
to learn implicitly (without gaining explicit knowledge) when 
subjects are given a graph of their progress toward the goal state 
(Sanderson, 1989). Within concept learning, there is some indi-
cation that stimuli in which spatial location of features is incon-
sistent (as in concepts with letters as features; Carlson & Du-
lany, 1985; Rosch & Mervis, 1975) may be harder for subjects 
to learn, but no experiment has specifically manipulated this 
variable. Within artificial grammar and sequence learning, sub-
jects show knowledge that is specific to location in the sequence.
Dienes et al. (1991) showed, with the sequential letters depen-
dency test, that subjects have knowledge of where in the string 
particular letters may appear. Subjects demonstrate higher lev-
els of knowledge of initial and terminal letter sequences than 
sequences in the middle of strings (A. S. Reber, 1967; A. S. Re-
found that subjects allowed to study freely have a bias toward 
combining the middle and initial chunks rather than the final 
one in a three-chunk string. In the Hebb digits task, changing 
the first two elements eliminates the effect, but changing other 
elements does not (Schwartz & Bryden, 1971).

There is much less evidence for temporal biases in implicit 
learning. Sequence learning experiments have demonstrated 
the induction of information across time, revealing that loca-
tion in time is a powerful means of indicating stimulus separate-
ness. However, little research has been conducted manipulating 
time intervals in implicit learning or specifically comparing 
temporal and nontemporal versions of tasks such as artificial 
grammars and contingent response tasks. McDowell et al. 
(1993) found that varying the interstimulus interval randomly 
in a serial reaction time task hurt learning, but no study has 
investigated the manipulation of intervals in a patterned way to 
determine whether it facilitates learning. There is evidence that 
subjects are limited in inducing patterns in which crucial ele-
ments are separated by irrelevant stimuli: Cleeremans and 
McClelland (1991) found that subjects induced over three but 
not four irrelevant items in artificial grammar structured serial 
reaction time, and Millward and Reber (1972) found that sub-
jects in a simpler two-event probability learning task learned 
contingencies across a lag of at least five and perhaps up to seven 
intervening irrelevant items. However, in cases in which the in-
tervening items are not irrelevant but contribute to the struc-
ture of the sequence, subjects can encode contingencies back an 
indefinite number of trials.

Hierarchical Processors and Pairwise Associators

A. Cohen et al. (1990) found a dissociation between learning 
pairwise associations and hierarchical representations in a se-
rial reaction time task. They used sequences in which there were 
two types of associations between adjacent elements: unique (in 
which each item is always paired with the same item) and am-
biguous (in which items are paired with more than one other item). 
These two types of associations led to three types of pat-
terns: unique (only unique associations, as in 13425), hybrid 
(unique and ambiguous pairings, e.g., 13212), and ambiguous 
(only ambiguous pairings, e.g., 132123). They found that, un-
der single task conditions, subjects learned all three types of se-
quence; however, ambiguous sequences were not learned under 
dual task conditions. They argued that this pattern of results
indicates that there are two mechanisms: nonattentential and attentional. The nonattentential mechanism functions under both single and dual task conditions and can learn unique and hybrid sequences but not ambiguous sequences. The attentional mechanism can learn all three types of sequences but is interfered with by the dual task. Curran and Keele (1993) extended these results, finding that less aware subjects trained on an ambiguous sequence in single task conditions did not show any implicit knowledge when transferred to dual task conditions. Subjects trained on hybrid sequences did transfer knowledge to the dual task condition. These results indicate that the dual task interfered with the expression of the higher order knowledge that had been gained during the single task conditions. A. Cohen et al. (1990) argued that the nonattentential mechanism is a linear associator that learns relations between adjacent pairs of stimuli but cannot learn ambiguous sequences because each stimulus is paired with each other stimulus. The attentional mechanism is a hierarchical processor that can learn higher order information about the sequence. Keele et al. (1990) suggested that the hierarchical processor learns higher order information about sequences by performing parsing on the input. Keele and Jennings (1992; Jennings & Keele, 1990) simulated learning using a recurrent network and found that introducing parsing of the sequences, either at the end of each cycle of the sequence (corresponding psychologically to dividing the sequence into parts) or by having different codes indicating subsequences (corresponding to the psychological process of assigning representational codes hierarchically), led to learning of ambiguous strings. However, Cleeremans and McClelland (1991) were able to account for differences in learning ambiguous and other sequences by adding nonspecific noise to their model, which implies that parsing may not be a required mechanism in learning ambiguous sequences and raises the possibility that an associative model can learn both kinds of sequences, obviating the need for two separate mechanisms.

Neural Substrates of Implicit Learning

It is possible to make some tentative suggestions regarding the brain areas that may be involved in implicit learning. So far, there is evidence that points to the importance of the basal ganglia, association cortex, and frontal cortex in implicit learning, in addition to some evidence for a role being played by the hippocampus. The basal ganglia appear to be involved in aspects of response programming, the association areas appear to be involved in perceptual aspects of implicit learning, and the frontal lobes appear to be involved in the evaluation of implicit knowledge in making conceptual fluency judgments. Table 7 summarizes the results of implicit learning tasks in patient groups that have damage in these areas. Implicit learning within any one task certainly involves activity in multiple brain areas and, hence, may involve learning within more than one area.

**Basal Ganglia**

The basal ganglia are a series of nuclei, sometimes called the striatum (along with the globus pallidus), that are located subcortically. The role of the basal ganglia in implicit learning has been investigated primarily through the study of people with Huntington’s disease or Parkinson’s disease. Both originally present themselves as motor impairments but progress to dementia. Huntington’s patients show damage to the basal ganglia, especially the head of the caudate nucleus (Bruyn, Bots, & Dom, 1979). Parkinson’s disease most severely affects the substantia nigra; nigrostriatal projections are lost and, hence, the activity of the basal ganglia is disrupted (Cummings & Benson, 1983, 1984). Independent of their overall motor impairment, Huntington’s and Parkinson’s disease patients show impairments in implicit learning. Huntington’s (Knopman & Nissen, 1991) and Parkinson’s (Ferraro et al., 1993) patients are impaired in learning sequence specific knowledge in the serial reaction time task and are impaired on motor skill learning in the pursuit rotor task (Heindel, Salmon, Shulman, Wallis, & Burtles, 1989). Several studies have investigated the Tower of Hanoi in these patient groups and have found that subjects with Parkinson’s disease and subjects with advanced, but not early, Huntington’s disease are impaired in learning the skill relative to their explicit memory ability (Butters et al., 1985; Saint-Cyr; Taylor, & Lang, 1988). In addition, Huntington’s and Parkinson’s patients are impaired at frequency monitoring, a task that does not involve motor response learning (Sagar, Sullivan, Gabrieli, Corkin, & Crowdon, 1988; Strauss, Weingartner, & Thompson, 1985; Sullivan & Sagar, 1989). This impairment, which may be related to deficits characteristic of patients with frontal lobe damage, is discussed in more detail later.

In addition, the basal ganglia appear to play an important role in acquisition of what Mishkin et al. (1984) called habit learning: learning to associate a given stimulus with a reward. Wang, Aigner, and Mishkin (1990) found that monkeys with lesions of the tail of the caudate and the ventral putamen were impaired on the 24-hr concurrent discrimination task, a test in which the monkey is presented once a day with a series of pairs of stimuli and learns which stimulus in each pair is baited. This task is usually compared with a nonmatching to sample task. Animals with caudate damage are unimpaired on the latter task but are impaired on 24-hr concurrent discrimination. Animals with hippocampal damage show the opposite pattern of deficits: no impairment (or even enhancement) on the 24-hr concurrent discrimination task but severe impairment on the nonmatching to sample task. Additional evidence for the involvement of the caudate in learning to make simple associations was provided by Packard, Hirsh, and White (1989), who found that caudate damage in rats impaired their ability to learn a win–stay strategy but did not interfere with their ability to learn a win–shift strategy. Habit learning in animals does not necessarily correspond to implicit learning in humans. Squire (1992) noted that animals appear to learn these tasks qualitatively differently than humans; animals may use a process akin to implicit learning for 24-hr concurrent discrimination, but humans rely on episodic memory for both. In addition, the habit learning evidenced here involves learning simple associations, not complex knowledge that characterizes implicit learning in humans. Habit learning nevertheless provides converging evidence for the importance of the basal ganglia for implicit learning.

**Association Areas**

The role of cortical association areas in implicit learning has been investigated in studies of subjects with Alzheimer’s dis-
Table 7

Implicit Learning Performance in Brain-Damaged Populations

<table>
<thead>
<tr>
<th>Task</th>
<th>Hippocampus (amnesia)</th>
<th>Frontal damage</th>
<th>Association areas (Alzheimer’s disease)</th>
<th>Basal ganglia (Huntington’s, Parkinson’s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artificial grammar</td>
<td>Normal</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Visuospatial concepts</td>
<td>Normal</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Covariation learning</td>
<td>Normal</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Serial reaction time</td>
<td>Normal</td>
<td></td>
<td>Most normal, a subset impaired</td>
<td>Impaired</td>
</tr>
<tr>
<td>Contingent response</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hebb digits</td>
<td>Impaired for long strings</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Puzzle learning</td>
<td>Mixed results</td>
<td>Impaired</td>
<td></td>
<td>Impaired</td>
</tr>
<tr>
<td>Motor learning</td>
<td>Normal</td>
<td>Normal</td>
<td></td>
<td>Impaired</td>
</tr>
<tr>
<td>Function matching</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dynamic systems Frequency</td>
<td>Normal initial, but impaired retention</td>
<td>Impaired</td>
<td>Impaired</td>
<td>Impaired</td>
</tr>
</tbody>
</table>

This disease, in its early phases, causes damage to cortical association areas (Rapoport, Horwitz, Grady, Haxby, & Schapiro, 1989), especially the medial and lateral surfaces of the temporal and parietal lobes (Brun, 1989). Research on Alzheimer’s patients indicates that the association areas are involved in perceptual representation: Alzheimer’s patients show impaired priming (Heindel, Salmon, & Butters, 1991; Nebes, 1989), and priming is believed to be due to increased activation in the perceptual representational system (Tulving & Schacter, 1990). Kosslyn and Koenig (1992) suggested a mechanism that may underlie implicit learning in the association areas: There may be two systems involved in parallel in perceptual representation, one that merges stimuli and extracts prototypes and another that stores individual exemplars. Both of these processes may be taking place in the association areas. The former corresponds to implicit learning and appears not to depend on the hippocampus; the latter corresponds to episodic learning and is hippocampus dependent. Hence, implicit learning could involve changes in association areas without requiring hippocampal input. Specifically, there is reason to believe that association areas may be involved in implicit learning of visual patterns that is accessible through the conceptual fluency response modality. However, further research is needed on the ability of subjects with Alzheimer’s disease to learn visual concepts.

As well as being involved in representation of visual concepts in the perceptual representation system, the association areas may be involved in other aspects of implicit learning. Alzheimer’s patients are impaired at making frequency judgments (Strauss et al., 1985), which is consistent with frequency being represented in the association areas along with representations of objects (but could also be due to frontal lobe involvement in Alzheimer’s disease; see later discussion). In addition, some studies have shown that Alzheimer’s patients are impaired on the serial reaction time task relative to nondemented elderly controls (Ferraro et al., 1993). However, Knopman and Nissen (1987) found that most Alzheimer’s disease patients are not impaired on the serial reaction time task; the subgroup that was impaired in their study also tended to be impaired on other spatial tasks, implying that their inability to learn the sequence was due to impairments in spatial cognition.

Frontal Lobes

The overall role of the frontal lobes in cognition is not well understood, but the existing evidence indicates that they play an important role in planning and judgment (Shallice, 1988) and in the use of retrieval strategies in memory (Moscovitch & Umiltà, 1991). The frontal lobes are related to the basal ganglia in that they are both part of a series of large loops in which information is funneled down from the cortex, to the basal ganglia, to the globus pallidus and substantia nigra, to the thalamus, and then finally back up to the frontal lobes (Alexander, DeLong, & Strick, 1986). Hence, it is not surprising that frontal damage and subcortical damage can lead to similar behavioral impairments (Taylor, Saint-Cyr, & Lang, 1990), such as impairment in the ability to solve the Tower of Hanoi. In the Tower of Hanoi, it is difficult to tease apart subjects’ difficulties in learning the task initially, which could be an impairment in explicit planning and problem solving that is dependent on the frontal lobes, from subjects’ impairment in implicitly learning patterns of moves during repeated solving of the problem, which may be mediated subcortically.

Several lines of research with frontal patients indicate that they have problems performing frequency and recency judgments (Milner, Petrides, & Smith, 1985; Shallice, 1988), as do subjects with Parkinson’s disease (Sagar et al., 1988; Sullivan & Sagar, 1989; Strauss et al., 1985). Amnesias with no frontal damage are unimpaired on frequency and recency judgments (Sagar et al., 1990), but Korsakoff’s amnesics are impaired (Strauss et al., 1985); their impairment may be due to the frontal damage associated with the disease, which leads to deficits in metacognitive judgments (Shimamura & Squire, 1986). To the extent that implicit learning and frequency learning overlap, it is reasonable to predict that the frontal lobes play a role in both and that patients with frontal damage would be impaired in implicit learning.
Frontal damage also leads to some impairment in making metacognitive judgments and, therefore, may interfere with the expression of implicit knowledge through the conceptual fluency response modality. As argued earlier, conceptual fluency involves both the changes leading to increased fluency and thought processes that evaluate the fluency and use it to make judgments. The latter process is similar to making metacognitive judgments, and the frontal lobes are likely to be involved. Janowsky, Shimamura, and Squire (1989) found that frontal patients were impaired in their ability to predict their likelihood of recognizing the correct answer to a question for which they could not recall the answer after a delay. However, it should be kept in mind that not all metacognitive judgments of knowledge are necessarily linked: Leonesio and Nelson (1990) showed that three different metacognitive judgments (judgments of memorability made before study, such judgments made immediately after study, and the ability to recognize the correct answer to a question answered incorrectly) were made independently; they did not correlate with each other. Hence, conceptual fluency judgments of implicit knowledge may be performed differently from both metacognitive and frequency judgments. Nevertheless, the difficulties of frontal patients in making these judgments represents converging evidence that the frontal lobes may be involved in making conceptual fluency judgments.

Hippocampus

The definition of implicit learning used in this article postulates that the hippocampus is not required for most implicit learning, and, in fact, the majority of research (reviewed in the introduction and in the Overview of Implicit Learning Tasks section) shows that amnesics perform well on implicit learning tasks. However, there are some interesting cases in which amnesics have proven incapable of learning tasks that, on the surface, look like they should involve implicit learning. For example, amnesics do not show savings in solving tactile mazes over trials (Cermak et al., 1973; Corkin, 1965; Nissen et al., 1989), even though they are practicing an identical motor pattern in each case that, one would expect, would be learned implicitly. Cermak et al. (1973) argued that maze learning requires verbal mediation but that explanation does not account for why Nissen et al. (1989) found no savings in maze learning when all side paths were blocked so that the task involved pure repetition of the same motor pattern. Nissen et al. suggested that amnesics could learn processes only when their response options were limited by the structure of the task at hand and that blocking the side paths from subjects did not prevent them from attempting to go down the path anyway. However, this explanation is not consistent with the demonstrated learning of amnesics in implicit learning tasks with several unconstrained response options, such as dynamic systems (Squire & Frambach, 1990). It should be noted that patients with frontal lobe damage also have trouble in solving mazes (Fuster, 1989; Milner & Petrides, 1984), but their deficits are probably due to lack of ability to plan and execute an initial solution rather than their inability to implicitly learn a pattern of moves.

Milner, Corkin, and Teuber (1968) found that the amnesic patient HM, if given very short mazes, did show savings across trials. This pattern of results in maze learning is similar to the pattern in the Hebb digits task, in which amnesics are impaired in learning digit strings longer (Charness et al., 1988; Milberg et al., 1988) but not shorter (Baddeley & Warrington, 1970) than their digit spans. The two tasks suggest that the hippocampus may be important for learning long sequences but that short sequences may be learned implicitly by nonhippocampal systems. Another possible explanation is in terms of the novelty of the stimuli: The Hebb digits task may be especially difficult because each string is identical in terms of elements (each digit from 1 to 9) and differs only in the order of the elements. Likewise, all mazes are composed of corridors and turns, without much in the way of differentiating features. Other implicit learning tasks involve much more novel or idiosyncratic information for the implicit learning process to use in forming unique representations.

Modeling Implicit Learning

Models of implicit learning processes can potentially illuminate the mechanisms underlying implicit learning. Dienes (1992) thoroughly evaluated the ability of different kinds of models to account for artificial grammar learning. He tested exemplar, feature array, and multiple trace memory array models and two connectionist autoassociators, one using the Hebb rule and one using the delta rule. He required the models to account for a range of experimental data: percentage correct, consistency of error, range of subject performance, and rank order of string difficulty. The only model that met all of these criteria was a delta rule autoassociator processing all letters of the string simultaneously. Ganis and Schendan (1992) found that a three-layer feedforward network using a Hebb rule could learn strings and match the frequency of errors and correct responses shown in A. S. Reber (1967). However, it is unclear how well their model can account for other experimental data.

Several researchers have used recurrent network models of the sort proposed by Jordan (Jordan & Rosenbaum, 1989) and Elman (1990) to model sequence learning. In both, later layers of the network feed back on input layers, allowing the network to detect sequential covariations. Cleeremans and McClelland (1991) found that a simple recurrent network could be used to model learning of artificial grammar structured sequences in serial reaction time. The original model was too efficient; however, when they accounted for factors such as long-lasting priming of responses and priming of sequential pairings of responses, their model accounted for human performance well. Kushner et al. (1991) found that this model could simulate a contingent prediction task. The model has been used to simulate the findings of A. Cohen et al. (1990), that unique and hybrid sequences were learned under dual task conditions but that ambiguous sequences were not learned, in two different ways. Keele and Jennings (1992; Jennings & Keele, 1990) argued that unique and hybrid sequences could be learned without parsing but that ambiguous sequences required parsing to be learned. They parsed sequences by dividing the sequence into parts (by setting the state units to zero at the end of each cycle of the sequence) and by assigning different plan units to each subpart of the sequence. Both techniques led to greatly improved learning of ambiguous sequences. On the other hand, Cleeremans and McClelland (1991) argued that the dual task merely made
learning more difficult overall, leading to impairment of learning of unique and hybrid sequences and eliminating learning of ambiguous sequences. They were able to model these results by simply adding noise to the input units.

Servan-Schreiber and Anderson (1990) proposed a model of artificial grammar learning based on a process of competitive chunking. Their model processes strings by chunking letter groups based on stored chunks in memory and creating new chunks through combination of old ones. Grammaticality of strings is determined by the amount of chunking that can be performed on a string. They found that their model accounted for the increased ability to memorize strings as more strings are learned and for results of their experiments that manipulated the chunks subjects formed through grouping of the letters in the learning set. It is unclear, however, whether their model can account for all of the data Dienes (1992) used as criteria.

In short, models, particularly connectionist models, have been successful in performing inductions on artificial grammars and sequences. Implicit learning is an area of cognition especially suited to being modeled by connectionist mechanisms: It is a process that learns from exemplars by inducing similarities and patterns in the input. However, there are some aspects of implicit learning that are not easily accounted for by connectionist models. It may not be possible to account for the biases in the implicit learning mechanism without adding unusual properties to the models. For example, would a connectionist model show the same bias toward induction of power functions as humans do?

Current connectionist models are also not able to account for subjects' abilities to transfer their knowledge to novel stimuli in which the surface structure is changed but the deep structure remains the same (Manza & Reber, 1992; Mathews et al., 1989; A. S. Reber, 1969). Connectionist models develop instantiated representations that are linked to the physical form of the stimuli, not abstract rules. Kushner et al. (1991) found that their model of a contingent response task accounted well for subjects' initial learning, but the model adjusted much more slowly than did human subjects to an alteration in the mapping of the rules to surface features. As discussed earlier in the section on representation, subjects' ability to transfer may be due to explicit analogical thought combined with instantiated implicit knowledge, but it may also be due to knowledge of abstract rules. Current connectionist models can account for neither possibility.

In addition, it is unclear how well connectionist models can account for the interaction of explicit thought with implicit learning. Clark and Karmiloff-Smith (in press) argued that connectionist mechanisms are useful in modeling implicit learning but that accounting for representational redescription (Karmiloff-Smith's proposed mechanism for how implicit knowledge is transformed into explicit knowledge, discussed further in the conclusion) will require either hybrid models (combining connectionist models with classic symbols models) or augmented connectionist models that can use their own representations as independent objects subject to further manipulation within other processes leading to higher levels of structured representation.

Models can be of most value in developing theories of implicit learning if they are used as an additional source of information in exploring basic issues in the field such as how dual task conditions affect implicit learning, what kind of biases are present in the mechanism, or whether and under what conditions transfer can occur between response modalities. Different mechanisms may lead to learning of different patterns; for example, a connectionist model using the delta learning rule may be able to learn concepts with exemplars that are similar to each other or that overlap because of the feedback component of the rule, but a model using the Hebb rule may not be able to do so, even if both models can learn nonoverlapping concepts.

The implicit learning literature suggests some cautionary points for those who wish to model implicit learning. For example, there are the three response modalities through which implicit learning is demonstrated and between which there often is no transfer. Modelers should be clear as to which process they are modeling. It is perhaps reasonable to take overall activation in the nodes as a measure of conceptual fluency knowledge, because conceptual fluency may be due to priming in high-level mental systems dealing with covariation calculation, but it is less justifiable as a measure of efficiency or prediction. In these cases, it may be more reasonable to assign specific nodes to represent the output node for each move and have the individual node with the highest activation value be the selected action. Learning should be modeled as taking place within a response modality, and care should be taken not to mix different tasks. Modelers should take into account the influences of working memory and other cognitive processing systems engaged in the study of stimuli because implicit learning may be qualitatively different depending on which of these systems are involved. Modelers may find that implementing the structure of information in these working memory systems into their models assists in model development because constraining the structure of the input to the system helps constrain learning by the model.

Conclusion

This article has analyzed closely the experiments that have been performed in implicit learning with the aim of illuminating the internal structure of the implicit learning process: the response modalities and stimulus structures involved, how implicit learning depends on attentional and working memory systems, how implicit knowledge is represented, and what might be the neural basis of implicit learning. The final section attempts to take a broader view of the field. It first considers the question of what a unified theory of implicit learning might look like. It then considers how implicit learning might be related to other unconscious cognitive processes and to explicit thought.

Toward a Theory of Implicit Learning

A complete theory of implicit learning will, of necessity, be complex. For example, it will need to account for how implicit learning uses information from many different cognitive processes as the basis for inducing abstract implicit knowledge. The sources of information available to the implicit learning process depend on how the stimuli are processed by the subject. In artificial grammar learning, for example, subjects typically study artificial grammar strings through a combination of looking at the string, repeating the string to themselves, and sometimes
looking away and trying to visualize the string. Therefore, subjects engage many processing mechanisms, such as the articulatory loop and visuospatial sketch pad, and all of these processes may serve as sources of information for implicit learning abstraction processes. The type of implicit knowledge acquired may depend on which of these processes are involved; for example, learning of hierarchical aspects of stimuli may require involvement of the articulatory loop. It is not necessary that implicit learning be a single, separable, modular process to which all of these streams of information feed; rather, there may be several sites of implicit abstraction that receive information from only one of these streams. The neural basis of implicit learning for these perceptually driven streams of information is likely to involve the association areas of the cortex.

In response modalities such as efficiency and prediction and control, the response aspects of the task may also serve as input to implicit learning processes. For example, in the serial reaction time task, subjects may use a record of the last few button presses stored in short-term motor memory as one of the bases for implicit learning. Other mechanisms involved could be the posterior attention system, which may maintain a record of the last few stimulus locations, and the articulatory loop, which may maintain verbal labels for the past few stimuli. The neural basis of implicit learning in tasks involving response programming may involve the basal ganglia. In the conceptual fluency response modality, the particular response made is not part of learning. Instead, conceptual fluency involves a separate mechanism, perhaps based in the frontal lobes, that evaluates the processing of stimuli and makes judgments based on fluency or some similar sort of activation change in the abstraction mechanisms involved in implicit learning.

Implicit learning produces abstract but possibly instantiated implicit knowledge, although the exact representation of this knowledge is unclear. Different implicit learning mechanisms may be sensitive to somewhat different information; for example, a mechanism that takes as its input information from the articulatory loop may be more sensitive to sequential dependencies than a mechanism working off of the visuospatial sketch pad. Implicit learning may involve changes in high-level perceptual representation systems in a manner similar to priming. Research investigating biases and dissociations in implicit learning and the dependence of these biases on the involvement of different attentional or working memory processes will help resolve the question of representation.

**Implicit Learning and Unconscious Cognition**

Describing different areas of unconscious cognition and characterizing their importance to cognition as a whole have been popular recent topics of debate in cognitive psychology. This section describes how implicit learning is similar or different from other areas of unconscious cognition and summarizes the implications of implicit learning for the question of the importance of unconscious cognition.

Implicit learning is one phenomenon among many that are characterized by a lack of full awareness of important aspects of performance. Other areas include implicit memory, automatic processes in procedural memory, and lack of privileged access to mental states. Some theorists have divided these phenomena into broad categories: Kihlstrom (1987) distinguished between unconscious phenomena based on declarative memory structures, which he called preconscious or subconscious (the difference between the two rests on whether a person is normally aware of these percepts, and, thus, priming of words is preconscious and clinical cases of dissociation are subconscious), and phenomena based on procedural memory structures (such as automatized procedural knowledge), which he called unconscious. A. S. Reber (1989) distinguished between the primitive unconscious and the sophisticated unconscious; the latter is dependent on previously acquired semantic memory, whereas the former is not.

The interrelation between implicit learning and implicit memory was discussed in the introduction, with the conclusion that there is no firm dividing line between the two and that implicit learning and implicit memory may be based on similar mechanisms. Nevertheless, they are different in terms of what is learned (verbatim verbal information, for the most part, in implicit memory and novel nonverbal patterns in implicit learning) and in the roles played by awareness and attention.

Another important area of the cognitive unconscious that has also already been discussed is unconscious procedural memory. Information about how to perform a task that may have, at one time, been conscious is compiled into a form that functions automatically and efficiently but without awareness on the part of performers as to how they are performing (Baars, 1988; Kihlstrom, 1987). As argued in the introduction, procedural memory is different from implicit learning, because implicit learning involves learning processes that at no time are conscious rather than conversion of conscious processes into automatic, unconscious ones. Baars (1988) reviewed the properties of processes that are unconscious in this sense and concluded that such processes, in comparison with conscious processes, are characterized by low errors and high speed, use specialized mechanisms that are relatively isolated and autonomous, and show little interference when operating simultaneously.

Within social and developmental psychology, there is a body of research that considers how much conscious access people have to their mental states and the factors that influence these states. The controversy revolves around whether people have privileged access to the contents of their own mind or whether they infer the contents in ways similar to how they infer other people’s mental states. Nisbett and Wilson (1977) reviewed many studies showing that people are often unaware of factors that influence their decisions and judgments or are unaware of the connection between factors and their responses. Gopnik (1993) provided evidence that 3-year-old children are often wrong in reporting their immediate past psychological states and make similar errors in reporting the states of others. Implicit learning may be involved in the development of some unconscious influences on thought; for example, Hill et al. (1989) argued that phobias, which sufferers acknowledge are irrational and which they cannot explain, may be acquired through implicit learning. Postulating involvement of implicit learning can easily explain why people might be unable to access the reasons for their behavior, because implicit knowledge gained in implicit learning is unavailable to consciousness. However, implicit learning may not be the only, or even the main, mecha-
anism through which people acquire information that they later act on without awareness of its influence on their behavior.

What is the importance of these unconscious cognitive processes to human cognition and behavior in general? Loftus and Klinger (1992) phrased the debate over the importance of unconscious cognition in terms of whether the cognitive unconscious is “smart” or “dumb.” They concluded, along with Greenwald (1992), that unconscious cognition exists but is not very sophisticated. They also concluded that there is no evidence for unconscious processing of verbal stimuli at a higher level than the single word, that unconscious processes cannot deal flexibly with novel situations, and that the unconscious does not necessarily do what is best for one. However, some disagree; Erdelyi (1992) argued that the question of the power of the cognitive unconscious depends on the strictness of one’s definition of consciousness. A strict definition omits much and implies that the unconscious is not very powerful, whereas a looser definition leads to a more powerful picture of unconscious cognition but also incorporates some effects only questionably labeled “unconscious.” With regard to implicit learning specifically, Lewicki et al. (1992) claimed that “unconscious information-acquisition processes are incomparably faster and structurally more sophisticated [than consciously controlled cognition]” (p. 796). However, some studies imply that subjects cannot always achieve optimal levels of performance through implicit learning (Estes, 1986) and that implicit learning develops gradually over time (Lewicki et al., 1989). It is probably too soon to attempt to resolve the issue of which type of learning—implicit or explicit—is faster or more complex.

**Interrelations Between Implicit Learning and Explicit Thought**

There are two ways of comparing the roles of implicit and explicit learning in cognition. One is to identify different realms in which each form of learning is operative. Another is to examine how the two processes work together within realms. Implicit and explicit learning need not be mutually exclusive; the two probably work together at least some tasks, if not most. Their relative importance probably varies from task to task and may also vary within task, depending on the stance taken by the learner. However, the two approaches bring up different important issues; therefore, they are treated separately here. This section is organized around three questions. First, are implicit and explicit learning specialized for learning particular stimulus types or for performance in particular situations? Second, do implicit and explicit learning interact? Finally, what mechanisms might underlie the conversion of implicit into explicit information?

**Specialization of implicit and explicit learning.** Implicit and explicit learning are potentially specialized in two ways. First, each may be specialized for learning particular types of information. Second, each may be specialized for performing in a particular behavioral context. In general, implicit learning research involves stimuli that the explicit learning system finds hard to learn; as was discussed in the section on stimulus structure, these include stimuli (a) with complex relationships (b) for which the parsing is unclear, or (c) in which the relationship to be learned is not salient. It is reasonable to conclude that implicit relative to explicit learning is specialized for learning these sorts of relationships; however, this is not to say that the explicit learning system is not capable of learning simpler stimulus structures, but only that it is hard to demonstrate implicit learning of these structures without accompanying explicit knowledge. If implicit learning is evolutionarily earlier than explicit thought, its original role probably included learning the simple relations in the environment that now (in humans) are usually learned through the episodic memory system. Explicit learning appears to be specialized for learning based on verbal information or simple stimulus structures discoverable by conscious hypothesis testing. For example, subjects do not learn biconditional rules well in incidental learning conditions, which are conditions in which implicit learning performs well (Abrams & Reber, 1988; Mathews et al., 1989). In addition, Mathews, Buss, Chinn, and Stanley (1988) found that subjects did not learn the Bouthilet concept (the rule “choose the word from the set that contains only letters in the puzzle word”) through incidental study of concept exemplars but did learn it when they used explicit hypothesis testing.

Implicit and explicit learning may be specialized for certain situations. Implicit learning may play a larger role in perceptual–motor learning or unstructured learning, whereas explicit learning may be used more in verbal interactions with the world and in structured learning situations, such as formal schooling. Psychology is a domain that shows a difference in subjects’ knowledge in different contexts that might be due to using implicit thought in one and explicit in another. Subjects often show misconceptions in their explicit knowledge of physics (Wellman & Gelman, 1992), such as predicting that an object released from a circular trajectory will continue to move in a curved line rather than correctly predicting that it will move in a straight line tangent to the curvature at the point it was released (Kaiser, Jonides, & Alexander, 1986). However, subjects demonstrate correct knowledge when they are tested with other tasks that may be more dependent on implicit thought. For example, when shown objects in motion and asked to discriminate possible from impossible motion, subjects show accurate knowledge (Kaiser, Proffitt, & Anderson, 1985; Shanon, 1976), at least if the objects involved behave as point masses; subjects do not show good knowledge of patterns of rotational movement (Proffitt, Kaiser, & Whelan, 1990). In addition, in the domain of projectile motion, subjects demonstrate the correct relationship between variables of height, speed, and distance when actually throwing objects but not when making explicit judgments about these variables (Krist, Fieberg, & Wilkening, 1993). Holyoak and Spellman (1993) suggested that subjects’ ability to correctly identify patterns of incorrect and correct motion is due to implicit learning of motion patterns, which is separate from their explicit theories of physical behavior, and that the two forms of knowledge are operative in different cognitive contexts. Implicit learning and explicit learning may be relied on to different degrees depending on the context in which the knowledge is used (whether in a formal environment, such as work or school, or an informal environment, such as recreational activity). The work or school environment may discourage dependence on implicit learning because one is expected to be able to justify one’s
conclusions, and conclusions based on implicit knowledge cannot be justified without conscious access to implicit knowledge.

In addition, implicit learning may be advantageous in conditions in which subjects must function under stress or split attention. Masters (1992) found that subjects taught golf putting under implicit conditions (in his experiment, a dual task situation) gained knowledge that was more resistant to emotional stress (the option of earning extra money if they putted well) than subjects who learned under conditions in which they developed explicit knowledge about putting.

Interaction of implicit learning and explicit thought. Many researchers in implicit learning have been interested in whether the explicit and implicit knowledge bases developed in their tasks are independent. This section reviews research on implicit learning that deals with the interaction between implicit and explicit thought and then reviews research on explicit thought that deals with instances in which subjects do and do not incorporate implicitly learned knowledge into judgments and concepts.

Are the knowledge bases developed in implicit learning separate from those developed in explicit learning? In dynamic systems research, subjects' explicit knowledge can be manipulated separately from their performance ability; verbal knowledge can even decrease as performance ability improves (Berry & Broadbent, 1988; Broadbent et al., 1986). Performance ability increases earlier than verbal knowledge of the task (Stanley et al., 1989). Good explicit knowledge results when the key variables are salient and the total number of variables is small (Broadbent et al., 1986); it also results from high degrees of practice and large solution spaces (Sanderson, 1989). In artificial grammars, explicit and implicit knowledge appear to be more closely related; Dienes et al. (1991) argued that they are based on the same knowledge base because experimental variables affect both of them similarly. However, one need not assume that the two types of knowledge have a common mental representation to account for these results; the separate, explicit knowledge base may be a veridical subset of the implicit knowledge.

Other studies have compared learning in subjects given implicit or explicit instructions in the same task. A. S. Reber (1976; Reber et al., 1980) compared subjects who studied strings using intentional or incidental instructions; it was assumed that subjects given intentional instructions used solely conscious hypothesis testing for their learning. In many cases, subjects given intentional instructions were worse at the well formedness test and showed evidence of having induced nonrepresentative rules, as measured by their inflated consistency of error when classifying repeated strings. This effect has often failed to replicate (Dienes et al., 1991; Dulany et al., 1984); whether the effect is found probably depends on experimenters' ability to ensure that subjects are really attempting to discover rules and not falling back on easier forms of processing such as simply observing the stimuli. A different approach to comparing implicit and explicit learning is to develop tasks in which one version leads subjects to learn explicitly and the other version leads them to learn implicitly. Hayes and Broadbent (1988) developed two versions of a dynamic system with the same cover story; one version used a simple, salient relationship between the variables and appeared to be learned implicitly, whereas the other version used a more complicated relationship and was learned implicitly. However, R. E. A. Green and Shanks (1993) found that the two tasks were learned in similar ways. In sum, it is possible to get subjects to emphasize implicit or explicit learning within a task, at least in some situations, but it is difficult (perhaps impossible) to develop a task that is process pure and involves only implicit or only explicit learning. Jacoby, Lindsay, and Toth (1992) argued, in the cases of implicit memory and unconscious perception, that one should try to investigate the relative contributions of conscious and unconscious processing through manipulations within the same task rather than by trying to develop tasks that are purely conscious or purely unconscious.

Do people, in fact, use implicitly acquired information in their explicit thinking? There is evidence that, in the face of strongly held explicit beliefs, knowledge gained through implicit learning is disregarded. Holyoak and Spellman (1993) noted that the phenomenon of base rate neglect (underusing base rate information in making judgments about the probability of individual events) can be seen in this light: Subjects appear to be ignoring their (possibly implicitly learned) knowledge of frequencies in favor of other information. However, as they noted, base rate information developed through real-world experience can be used appropriately in making decisions (Christensen-Szalanski & Bushyhead, 1981). Holyoak and Spellman concluded that base rates are learned by subjects but that whether subjects rely on them or on individualizing information in the stimulus depends on the nature of the explicit task they are performing.

The neglect of information available from the stimuli in favor of maintaining theory is also seen in concept use and formation. Murphy and Medin (1985) argued that theories are an important part of conceptual structure and that concept formation is not merely theory-neutral feature tabulation. Chapman and Chapman (1967) investigated the tendency that psychiatrists had toward correlating certain projective psychological test signs with homosexuality, even though empirical research and the cases that they observed in practice showed no such correlation. They had naive undergraduates study draw-a-person test results and found that these subjects discovered the same illusory correlations as the psychiatrists. These correlations corresponded to the guesses of naive subjects with no experience with actual test results. The authors concluded that preexisting biases can persist even in the face of massive contradictory evidence. Goldberg and Rorer (1972) extended these results, finding that there was a substantial decrease in illusory correlation after extensive training with exemplars but that subjects still showed substantial bias. Hamilton and Rose (1980) found that subjects remembered a higher proportion of stimuli that were congruent with their stereotypes and a smaller proportion of stimuli that were incongruent. However, having a theory can be helpful in some situations: Wright and Murphy (1984) found that preexisting beliefs enhanced subjects' sensitivity to covariations by reducing the effects of outliers; subjects with an incorrect theory actually performed better than subjects presented with the same stimuli in a neutral context. It is unclear to what these differing results should be attributed; the influence of implicit learning on explicit concept formation may depend on several factors, including the strength of the conceptual theories and the sa-
licience of the disconfirming, or lack of confirming, evidence (Hamilton & Rose, 1980; Lewicki et al., 1989). In addition, even if implicit learning does not usually have the power to change an already-established theory, it may nevertheless play an important role in theory genesis.

*Conversion of implicit to explicit knowledge.* Are there situations in which implicit and explicit knowledge can be developed together or implicit knowledge can be converted into explicit knowledge? It has already been shown that, within implicit learning research, the conceptual fluency response modality evaluates implicit knowledge and makes explicit judgments based on it. However, the underlying knowledge remains implicit. One might hope that implicit knowledge can be transformed into explicit knowledge, because there is evidence that implicit learning results in representations that are not flexible: People do not have access to components of the knowledge that they can use for other purposes (Holyoak & Spellman, 1993). The information learned may be linked to the responses made in the task and cannot be transferred to other responses (Stadler, 1989; Treisman, 1992). Implicit learning may also be inflexible because of its nonhippocampal base (see introduction); Squire (1992) argued that the hippocampus is needed for flexible knowledge representation. If implicit knowledge can be converted or redescribed into explicit knowledge, then the knowledge can be used in a wider range of contexts. This section first evaluates how implicit and explicit knowledge may be developed together, including through intuition, and then describes models that have been proposed to account for rede
description of implicit representations into explicit representations.

In the studies discussed in the preceding section, knowledge gained through implicit learning was often pitted against conflicting explicit knowledge, with the result that implicit knowledge was disregarded. However, in situations in which implicit and explicit processes are in concordance rather than conflict, they may be able to work together to achieve performance that is better than that produced by either one alone. In the area of artificial grammar learning, A. S. Reber et al. (1980) found that explicit instruction regarding the rules of the grammar helped subjects if it was combined with implicit, observational learning but that it was poor alone. Sense and Sterman (1992) described a business education system in which explicit identification of crucial variables and explicit prediction was combined with implicit learning through interaction with a dynamic system simulating a complex business situation. They found that if students were allowed to skip the explicit portion of the learning process, they would play with the simulation and often perform well; however, they did not develop insights that could be applied to further situations. The philosophy that implicit learning needs to go along with explicit learning is assumed in theories of education that propose that students learn by doing, not just by passively absorbing information (Lee & Gelman, 1993). Implicit learning may provide a “feel” for how a particular system works that allows people to perform well, whereas explicit learning may allow for transfer of knowledge to new situations.

A. S. Reber (1989) suggested that implicit learning may allow cognitive psychology to reclaim intuition (i.e., an introspectively sudden insight, the origin of which cannot be explained) as a psychological process. Bowers, Regehr, Balthazard, and Parker (1990) discussed the role of intuition in hypothesis discovery. They viewed intuition as a process in which there is a continual buildup of unconscious, coherent information that eventually passes some threshold of coherency and suddenly enters the person’s awareness. It seems sudden or abrupt to the experimenter but is, in reality, continuous in its development. As discussed earlier in the section on response modalities, subjects can develop explicit knowledge about stimuli through a sudden, unexplainable realization that there is a pattern, or even that there is a particular pattern present (Galanter & Smith, 1958). This explicit knowledge may be triggered by the buildup of implicit knowledge due to implicit learning processes but may also be a consequence of an independent process (Willingham et al., 1989).

In developmental psychology, Karmiloff-Smith (1986, 1990; Clark & Karmiloff-Smith, in press) has proposed a process that she has termed representational redescription to account for the conversion of implicit knowledge into explicit knowledge. It should be noted that her definition of implicit is the broader one characteristic of developmental psychology and discussed in the introduction (namely, all innate processing mechanisms); nevertheless, a similar process may redescribe knowledge that is learned by the implicit learning processes considered here. In her theory, implicit knowledge is modular and inflexible; it cannot be altered or serve as an input for other procedures. Representational redescription is an automatic process that operates on implicit representations that are well learned and efficient and transforms them. There are many layers of redescription in her model; knowledge can be redescribed several times before it becomes explicit or stable. Redescription results in the formation of knowledge structures that have greater flexibility (e.g., within the domain of drawing, children become capable of drawing a man with two heads) and are accessible to consciousness (e.g., children gain metalinguistic knowledge as an addition to unconscious linguistic knowledge).

J. M. Mandler (1992) has developed a similar, simpler theory of how infants can progress from purely perceptual concepts to ones that are truly conceptual in that they go beyond the information given in the percept. She postulated a mechanism that takes a spatial structure such as a prototype and makes a conceptual structure, called an image schema. The image schema is intermediate between induced perceptual commonalities and linguistic concepts. One example of an image schema is the concept of animacy, which Mandler argued can be formed through a transformation of knowledge of perceptual patterns of movement. Her model differs from Karmiloff-Smith’s in that her process is attentive and optional, not automatic, and does not require that implicit knowledge be mastered before being redescribed.

*A Final Comment*

The view of implicit learning that has emerged is one of a complex process; this complexity is seen in the conclusions that have been drawn here. Implicit learning uses many different stimulus types with widely differing underlying structures. It is measured through three different response modalities (conceptual fluency, efficiency, and prediction and control) that may correspond to separate learning mechanisms. Implicit learning,
depends on attention and working memory processes, and the quality and quantity of learning that results may depend on which of these processes are used during learning. Implicit knowledge is stored as abstract, and possibly instantiated, representations rather than aggregate or verbatim representations. Implicit learning shows biases toward different stimulus structures and dissociations between different mechanisms involved. It may involve several different neural areas, including the basal ganglia, association areas of cortex, and frontal lobes. Finally, implicit learning interacts with explicit learning and other cognitive processes in complex ways. This complexity indicates that any theory or model of implicit learning will also need to be complex; this is not necessarily the disadvantage it would appear to be at first, because each feature can provide constraints for the theory. However, it does mean that researchers doing experimental work, theorizing, or modeling within the field of implicit learning need to respect this complexity and resist the temptation to oversimplify.

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