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Using Immediate Memory Span to Measure Implicit Learning[1]

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Abstract. Implicit learning is the process of acquiring knowledge about the structure of a complex stimulus environment largely independent of conscious awareness of either the process or the products of acquisition. In the present study, a new method of measuring implicit learning using immediate memory span capacity was developed. This method avoids many of the conceptual and methodological pitfalls found in standard implicit learning tasks. Subjects were presented with sequences that had been generated by an artificial grammar and were asked to reproduce the sequences by pressing buttons on a customized response box. After being exposed to these sequences, subjects showed a selective increase in memory span for novel sequences governed by the same grammatical constraints, despite being largely unable to display explicit knowledge about grammatical sequences in a recognition memory test. Individual differences in the degree of implicit learning co-varied with general measures of memory span, indicating that individuals with larger immediate memory capacity are better able to learn and subsequently exploit the higher-order sequential dependencies that compose the structure of an artificial grammar. Implications for current models of implicit learning, the relationships between immediate memory span and sequential learning, and individual differences in implicit learning and language processing are discussed.

Introduction

Implicit learning has been defined as the process by which knowledge about the structure of a complex stimulus environment is acquired largely independent of conscious awareness of either the process or the products of acquisition (Reber, 1997a). This mechanism of automatic, non-conscious, non-reflective, non-analytic absorption of information from the environment is ubiquitous in human experience. Implicit learning has been thought of as a general, domain-free learning mechanism for inducing regularities about patterned relationships in a stimulus environment. Furthermore, the implicit learning process works in parallel with, not in the absence of, explicit cognitive processes: While explicit attention is paid to highly salient elements in the environment, information about structural regularities underlying those elements can be induced implicitly (Winter & Reber, 1994). Real world examples of implicit learning include learning appropriate social behaviors, complex procedures, and, perhaps most importantly, natural languages. Indeed, interest in the basic mechanisms of language learning led directly to the development of early laboratory methods for studying implicit learning (Chomsky & Miller, 1958; Miller, 1958; Reber, 1967).

This introduction is organized into several sections. The first discusses distinctions and commonalities among implicit and explicit learning and memory, which are related constructs distinguished in terms of the processes engaged in during encoding and retrieval. The development of finite-state languages (i.e., artificial grammars) and the emergence of implicit learning research are discussed. The second section highlights significant studies from the implicit learning literature that surround three central controversies: whether learning in an implicit learning task truly occurs largely independent of conscious awareness, whether the resulting knowledge base is an abstract system of rules or an instance-based set of exemplars, and ultimately whether distinct, dissociable modes of human learning even exist. The third section outlines a model of the cognitive unconscious based on principles from evolutionary biology, proposed by Reber (1992a, 1992b, 1993; also Reber & Allen, 2000), which predicts that implicit cognitive processes are not as susceptible to individual differences as explicit cognitive processes. The few studies that specifically investigate individual differences in implicit learning are then reviewed.

The final section argues that failures to find systematic variations in performance among individuals in implicit learning tasks can be attributed to several conceptual and methodological problems. With the exception of a few recent studies (e.g., Destrebecqz & Cleeremans, 2001), research on implicit learning has widely assumed that tasks are "process-pure" – that a given task exclusively involves either implicit or explicit knowledge. A new method for measuring implicit learning is proposed, based largely on assumptions from the process dissociation procedure (PDP; Jacoby, 1991), for separating the contributions of implicit and explicit processes in a given task. Finally, it is suggested that a measure of individual differences in implicit learning might be useful in explaining and predicting individual differences in cognitive abilities that are assumed to rely on implicit mechanisms (e.g., individual differences in language abilities).

Implicit and Explicit Learning and Memory

Implicit memory can be defined as the facilitation of task performance through prior experiences in the absence of conscious or intentional recollection of those experiences (Graf & Schacter, 1985). More specifically, a test of implicit memory does not make explicit reference back to the original study phase (Schacter, 1987), whereas a test of explicit memory does. A classic example of a test of explicit memory is a traditional recognition memory task, where subjects first study a list of items (most often, a list of words) and later are asked to decide whether a given item occurred on the original study list (e.g., Mandler, 1980). In principle, a recognition memory task requires the subject to consciously recollect some part of the original study phase. This methodology may be contrasted with some classic examples of implicit memory tests, such as word fragment completion and anagram solving. In a word fragment completion task, subjects study a list of words (as they would in a recognition memory task) and later are asked to identify words presented in a degraded or altered form. For example, the word METAL could be presented in "visual noise", with some proportion of the orthography masked or deleted (Warrington & Weiskrantz, 1970); the word could be presented as _e_al, with some of the letters missing (Roediger, Weldon, Stadler, & Riegler, 1992); or the word could be presented as an anagram, such as EMTLA (Jacoby & Dallas, 1981). The general finding from these studies is that prior presentation of a word during the study phase improves subjects' ability to identify the degraded or altered word during the testing phase, a phenomenon known as priming (Tulving & Schacter, 1990). The task of identifying a word fragment or unscrambling an anagram does not require the subject to consciously recollect the original study phase, yet their prior exposure to the target word during the study phase has an implicit influence on their ability to identify the word during the testing phase.

Interest in the dissociations between implicit and explicit memory emerged primarily from the study of the amnesic syndrome, in which any of a number of forms of brain damage can impair memory functioning while leaving other cognitive functions intact (Roediger, 1990b). Landmark research by Warrington and Weiskrantz (1968, 1970) challenged the view that amnesic patients lacked the ability to transfer verbal information from short-term to long-term memory by demonstrating intact long-term memory in amnesic patients on implicit memory tests. Warrington and Weiskrantz (1970) compared amnesic patients and control subjects in their performance on free recall, recognition, word fragment identification, and word stem completion tests. In both the free recall and recognition memory tests (tests of explicit memory), control subjects performed better than amnesic patients. Of course, poor (explicit) memory performance is a defining feature of the amnesic syndrome, so this finding was not surprising. However, the amnesic patients performed just as well as control subjects on the word fragment identification and word stem completion tests, the tests of implicit memory.

Based on the findings of Warrington and Weiskrantz, numerous researchers have argued that amnesic patients do not lack the ability to transfer verbal information from short-term to long-term memory, but instead have difficulty when asked to consciously retrieve such information. Evidence for dissociable forms of human memory is not limited to neurologically impaired populations alone: Dissociations between implicit and explicit forms of memory have also been demonstrated in normal human populations (reviewed in Roediger & McDermott, 1993). While some theorists have postulated distinct memory systems in the brain to explain these dissociations (e.g., Squire, 1987), others have proposed that these dissociations reflect different retrieval processes (e.g., Jacoby, 1983, 1988; Roediger, 1990a, 1990b). That debate aside, in simplest terms, implicit memory involves unconscious retrieval, while explicit memory involves conscious retrieval.

While explicit memory refers to the conscious recollection of past events, explicit learning can be characterized as the conscious, deliberate, analytical process used in discovering a rule (or sometimes a set of rules) that governs a set of stimuli. One classic example of an explicit learning task comes from Bruner, Goodnow, and Austin (1956), who applied a hypothesis-testing model to concept learning. In this study, subjects were presented with pictures that could be defined in terms of a number of relevant attributes, such as shape, color, and number of features. The pictures either were or were not members of a category, and membership in the category was based on a logical rule. For example, the stimuli in an experiment of this type could be pictures of flowers. A logical rule that would define membership in the category might be: “If a flower is red and has three petals, it is a member; otherwise it is not.” The experiment would progress as follows: Subjects were given a picture and had to decide whether the picture was a member of a category or not. After making a decision, subjects were told whether or not the picture belonged to the category and then were given another picture. Thus, for the first few stimuli, subjects simply had to guess about the membership of the stimulus. As the experiment progressed, however, subjects would eventually learn the rule that determines category membership (i.e., the concept) and begin using the rule to guide their decisions. Learning, in a typical experiment from Bruner et al.’s study, is explicit because it involves the systematic, analytic testing of specific hypotheses – that is, learning is explicit.

Researchers interested in how humans learn about complex stimulus domains, however, were not satisfied with the simplistic, well-defined, artificial structures used in early concept learning tasks like those of Bruner et. al. (1956). Clearly, simple logical rules are not representative of the complex rules that govern, for example, a natural language. One attempt to create a small-scale model of linguistic rules (which would end up being widely influential) was the finite-state (or artificial) grammar. An artificial grammar is an “algebra” for generating well-formed (“grammatical”) strings of symbols according to explicit rules (Chomsky & Miller, 1958). A diagram of an artificial grammar, used in an early experiment by Reber (1967), is shown in Figure 1. The numbered circles represent the states of the system, the arrows represent the permissible transitions from state to state, and the letters associated with each arrow represent the symbols generated by moving from one state to the next. Together, the system of states and transitions can be thought of as the “syntax” of the artificial language, and the particular letter set instantiated on the syntax can be thought of as the “vocabulary” of the artificial language. All well-formed strings in the artificial language are generated by starting at the input state and following any path through the diagram that ends at the output state. Although the complex grammar of English cannot be stated in such simple terms, these finite-state grammars were originally used as “miniature linguistic systems” to model language users (Chomsky & Miller, 1958; Miller & Chomsky, 1963).

One of the first important studies in artificial grammar research was done by George Miller (1958). Miller was inspired by the concept formation studies done by Bruner, Goodnow, and Austin (1956) and assumed that grammar learning could primarily involve the application of hypothesis formation and testing routines to experienced language productions. That is, the grammar of a language could be learned through an essentially explicit, analytical procedure analogous to the procedure used in concept formation tasks.

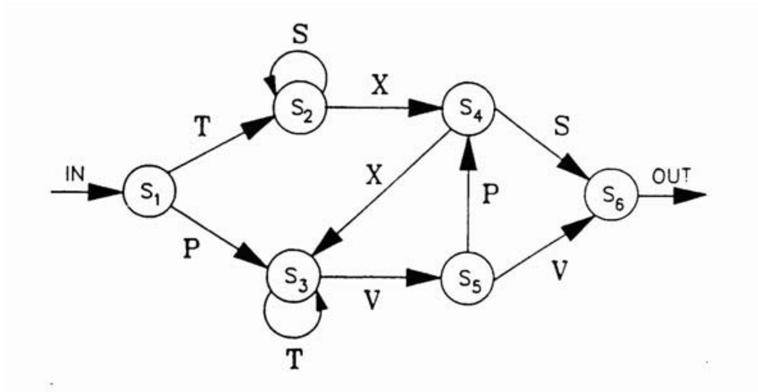

Figure 1. The artificial grammar originally used in Reber (1967). Grammatical letter strings are generated by moving through the grammar along the transitions from the input state (S_1) to the output state (S_6), and acquiring a letter with each transition.

To investigate this, Miller tested the hypothesis that familiarity with a system of grammatical rules might facilitate free recall. In his experiment, subjects were presented with a list of 9 letter strings, each ranging from 4 to 7 letters in length. One list contained strings that were formed with a random number table, while the other list contained strings formed by an artificial grammar (a grammar similar to, but less complex than the grammar shown in Figure 1). The letter strings were presented visually, one at a time, and subjects were given 5 seconds to memorize each string. Following the presentation of the entire list (all 9 strings), subjects were asked to recall, in any order, as many of the letter strings as possible. Subjects were given 10 trials with the same list of letter strings.

Miller found that the list of grammatical strings was learned much more quickly than the list of random strings: By the end of 10 trials, subjects recalling grammatical strings were able to recall on average almost all 9 letter strings, while subjects recalling random strings were able to recall on average only about 3 letter strings. Miller concluded that because letter strings generated by an artificial grammar were more redundant and carried less information than random letter strings, subjects were better at recoding the grammatical sequences into “chunks,” thus reducing the difficulty of the task (Miller, 1958; also Miller, 1956). Miller’s 1958 study was the only paper published on his artificial grammar learning research program, which Miller called “Project Grammarama” (Miller, 1967). Miller eventually abandoned Project Grammarama, feeling that the task of memorizing letter strings was terribly boring and that, ultimately, artificial grammar learning was conceptually limited. Miller believed there was insufficient common ground between his artificial grammar experiments and natural languages to make generalizations from one to the other (Miller, 1967).

Arthur Reber, however, believed otherwise. Reber became fascinated with the apparent ease with which subjects could classify letter strings as grammatical or non-grammatical after being exposed to a small subset of strings produced by an artificial grammar. In contrast to the explicit encoding explanation proposed by Miller (1958), where active, conscious, explicit processes are employed to discover grammatical rules, Reber had the intuition that passive, unconscious, “implicit” processes could be responsible for learning grammatical rules. Reber (1967) put his intuition to the test in a landmark study. His first experiment was a replication of Miller’s (1958) study comparing free recall of letter strings generated randomly versus letter strings generated by an artificial grammar (see Figure 1). Reber replicated Miller's finding that grammatical letter strings were easier to learn and remember than random letter strings. However, Reber doubted Miller's explicit encoding hypothesis, saying, "It is not at all clear that an encoding system which is simple enough to discover yet efficient enough to facilitate learning even exists" (Reber, 1967, p. 859). Reber argued that if subjects were explicitly recoding individual symbols into larger "chunks," then they should have at least some verbalizable knowledge about the grammatical rules underlying the letter strings. However, when Reber informed subjects that the letter strings had been generated according to a complex system of rules and asked them to describe what they knew about the rules, subjects were unable to verbally express explicit knowledge about the rules of the grammar, even when asked specific questions about the letter strings (e.g., "What letter or letters may letter strings begin or end with?").

To further investigate whether the rules of the grammar were encoded in an explicit/analytic or implicit/non-analytic scheme, Reber conducted a second experiment, which would become the standard artificial grammar learning experiment for future implicit learning research. The experiment consisted of two phases, a learning phase and a testing phase. During the learning phase, subjects were asked to memorize 20 letter strings generated by an artificial grammar. The letter strings were presented in four sets of five strings, and the criterion for learning was two consecutive correct reproductions of a set. During the learning phase, subjects were not told that the letter strings followed any system of rules and were not informed that there would be a testing phase later in the experiment.

After completing the learning phase, subjects were told that the 20 letter strings they had just learned were formed according to a complex system of grammatical rules, though no information was given about the nature of the rules. Subjects were then presented with a series of novel letter strings and required to decide whether or not each of the strings followed the grammatical rules. Subjects were not given feedback about their decisions. Half of the novel letter strings were randomly generated and thus non-grammatical, while the other half of the letter strings were new grammatical strings that had not been presented during the learning phase. Reber found that subjects could classify the novel letter strings as grammatical or non-grammatical well above chance and, furthermore, subjects did not display any explicit, verbalizable knowledge about the rules of the grammar when questioned following the experiment. Reber concluded that subjects were able to learn about the structure underlying grammatical letter strings "without recourse to explicit strategies for responding or systems for recoding the stimuli" (Reber, 1967, p. 863). Subjects could then apply this implicit knowledge in a transfer task to discriminate grammatical and non-grammatical strings and, ultimately, could not verbally express their knowledge about any of the grammatical rules that were used to generate the sequences.

Before proceeding to review the developments in the field of implicit learning since Reber's (1967) seminal study, it is now useful to draw some preliminary distinctions between implicit and explicit learning and memory. The best method for distinguishing these related constructs is to consider the processes engaged in during encoding and retrieval (following Stadler & Roediger, 1998). This framework is presented in Table 1. As described earlier, implicit memory refers to facilitation in task performance without conscious recollection, while explicit memory refers to situations that require conscious recollection. Stated in terms of the encoding-retrieval distinction, explicit memory involves the conscious and deliberate retrieval of information, while implicit memory involves unconscious and non-deliberate retrieval. However, both implicit and explicit memory involve intentional, explicit encoding of information (e.g., studying a list of words). Like explicit memory, explicit learning involves analytic encoding (the discovery of a rule) and intentional retrieval (consciously applying the rule to new stimuli). Implicit learning, as of now defined only in terms of Reber's artificial grammar learning task, involves unintentional, non-analytic encoding of structural regularities in a stimulus environment. However, the testing phase in Reber's task makes explicit reference back to the original study phase (c.f., Schacter,

1987) by requiring subjects to make deliberate, explicit judgments about letter strings. Thus, the artificial grammar-learning task requires intentional retrieval of information. One cell in Table 1 remains empty: We have not yet described a situation where the encoding of information is largely unconscious and non-analytic, and the subsequent retrieval of that information is unintentional and non-deliberate.

Encoding	**Retrieval**	
	Conscious, Deliberate	Unconscious, Non-deliberate
Intentional, Analytic	Explicit Learning Explicit Memory	Implicit Memory
Unintentional, Non-analytic	Implicit Learning	

Table 1. Implicit and explicit learning and memory, characterized in terms of the processes engaged in during encoding and retrieval.

"What Is Learned" and "How It Is Learned"

Reber's research program on implicit learning went largely unnoticed until the late 1980's, when, for a number of reasons, implicit cognition received renewed interest. Several important papers relevant to implicit cognition were published around this time, concerning implicit memory (Schacter, 1987), dissociable memory systems (Squire, 1987), the cognitive unconscious (Kihlstrom, 1987), and a new laboratory technique, the serial reaction time task (SRT; Nissen & Bullemer, 1987), which would become just as popular as artificial grammar learning in the study of implicit learning (see Hsaio & Reber, 1998, for a review). Much of the renewed interest in implicit learning has been centered around two points of controversy, which will be called the "what is learned" and the "how it is learned" issues. Controversy surrounding these issues has emerged largely from Reber's claims that the process of implicit learning occurs largely outside of conscious awareness and that implicit learning yields a tacit knowledge base that is an abstract representation of the system of rules (Reber, 1989, 1993). Opponents of these views have argued that there is not sufficient evidence to support the claims that learning is unconscious and abstract (Dulany, Carlson, & Dewey, 1984, 1985; Perruchet & Pacteau, 1990, 1991). One extensive review and criticism of implicit learning concluded that dissociable forms of human learning do not exist (Shanks & St. John, 1994). This section reviews some of the literature surrounding the "what is learned" and "how it is learned" issues and suggests that much of this controversy stems from the process-purity assumption found throughout the implicit learning literature – that is, the assumption that a one-to-one mapping exists between a given task and an underlying process.

To address the "what is learned" issue, Reber (1969) conducted a follow up to his original study to assess the extent to which implicit learning is the acquisition of knowledge about the superficial physical form of the stimuli versus knowledge about the deeper, more abstract relations that underlie them. The study consisted of two sessions during which subjects memorized letter strings generated from an artificial grammar. Reber investigated the effects of changing certain aspects of the artificial grammar (the syntax, the vocabulary, or both) during the second session of the experiment. Subjects were assigned to one of four conditions. In the first control condition, neither the syntax nor the vocabulary were changed during the second session. In the second condition, the letter set (the vocabulary) remained the same, but the syntax, the system of rules governing the letter strings, was changed. In the third condition, the syntax remained the same, but the vocabulary was changed. Finally, in the fourth condition, both the syntax and the vocabulary were changed in the second session. The various manipulations had systematic effects on subjects' ability to memorize letter strings in the second session. When neither syntax nor vocabulary changed, subjects showed steady-state performance – that is, learning transferred from session one to session two. When both syntax and vocabulary changed, subjects showed a decrement in performance – learning did not transfer to session two. The most interesting finding, however, was that changing the physical form of the stimuli (changing the vocabulary) did not have an adverse effect on the transfer of learning – learning could be transferred across letter sets. On the contrary, changing the system of rules governing the stimuli (changing the syntax) produced a decrement in performance in session two. These findings support the argument that the implicit knowledge acquired in the first session was abstract and did not depend on the physical form of the stimuli. Reber concluded that implicit learning was the abstraction of the deep structure, the syntactic system of rules that governed the stimuli rather than simply the learning of the explicit symbols of the surface patterns.

Several other studies have also employed transfer of learning paradigms to argue that implicit learning is a process of rule abstraction that is not tied to the physical form of the stimulus. A study by Mathews, Buss, Stanley, Blanchard-Fields, Cho, and Druhan (1989) replicated and extended Reber's original finding that implicit learning can transfer across letter sets. Mathews et al. tested subjects in an artificial grammar-learning task over a period of four weeks. Subjects who received a new letter set each week of the experiment, without any change to the underlying syntax, performed just as well as subjects who worked with the same letter set throughout the four-week period. Mathews et al. described this transfer across vocabularies as occurring "immediately and automatically without any conscious translation process."

Two other artificial grammar learning studies demonstrating transfer across sensory modalities are also worth mentioning here. Altmann, Dienes, and Goode (1995) presented subjects with sequences of auditory tones during the learning phase and then had subjects make grammaticality judgments about sequences of visually presented letters during the testing phase. They found that exposure to the grammar in the auditory modality improved classification of novel stimuli in the visual modality. In a more complex series of experiments, Manza and Reber (1997) compared cross-modal transfer conditions (from visual learning to auditory testing, and vice versa) with within-modality conditions. Manza and Reber found no differences between subjects in these four conditions in their ability to classify strings during testing. Together, these two transfer of learning experiments provide support for the "abstractionist viewpoint," that is, that implicit learning involves the abstraction of deep structure out of a stimulus environment.

Critics of the abstractionist view have developed innovative ways of demonstrating that fragmentary knowledge about memorized letter strings can explain classification performance in an artificial grammar-learning task. In a study by Dulany, Carlson, and Dewey (1984), subjects were given an artificial grammar learning task, following the standard Reber procedure, except that during the testing phase subjects were asked to specify the feature or features of each test string that led them to classify it as they did. That is, for items that were judged grammatical, subjects were asked to underline the letter or letters they felt made the item grammatical; for items they felt were not grammatical, subjects were asked to cross out the letters that rendered the string non-grammatical. Consistent patterns were found between subjects' grammaticality decisions and the portions of the strings they indicated as guiding those decisions. Based on these findings, Dulany et al. argued that subjects were not making their decisions based on any abstract representation of rules, but instead were basing decisions on knowledge about particular fragments in the test strings.

In a related study, Perruchet and Pacteau (1990) also claimed that subjects did not induce abstract representations of the artificial grammar but, instead, established fragmentary representations based on patterns of bigrams. To support their argument, Perruchet and Pacteau used two different learning techniques. One group of subjects studied a list of whole letter strings, while another group of subjects studied a list of frequently occurring permissible bigrams. Perruchet and Pacteau found that both groups were able to classify grammatical and non-grammatical test strings above chance and concluded that Reber's abstractionist view was unfounded. If subjects could classify strings better than chance after being exposed only to permissible bigrams, then it was likely that subjects' resulting representations were fragmentary as well.

Finally, Brooks and Vokey (1991; Vokey & Brooks, 1992) presented what is perhaps a compromise in this debate. They argued that grammaticality judgments can be made reliably without having a purely abstract representation; instead, all that is needed is an "instantiated memory" consisting of specific items and a decision making process based on a similarity metric. Brooks and Vokey examined performance in an artificial grammar-learning task while factoring in the physical and structural similarity of the test items. In the testing phase, subjects were presented with four types of strings: "close-grammatical" strings (i.e., ones that were physically close to a string memorized during learning and conformed to the rules of the grammar), "far-grammatical" strings (i.e., ones that differed by two or more elements from a memorized string and conformed to the rules of the grammar), "close-non-grammatical" strings (i.e., ones that were physically close to a learning string but violated the rules of the grammar), and "far-non-grammatical" strings (i.e., ones that were physically remote from learning strings and violated the rules of the grammar). Brooks and Vokey found that roughly half of the variance in subjects' performance could be attributed to each underlying factor, physical and structural similarity. Based on these results, Brooks and Vokey concluded that subjects were using both abstract and concrete representations to classify test strings.

To address the "how it is learned" issue, Reber (1976) manipulated the instructional set given to subjects in his artificial grammar learning task. One group of subjects was given a "neutral" instructional set, replicating the procedure of his original study (Reber, 1967). A second group of subjects was informed that a rule system governing the stimuli existed. These subjects were encouraged to search for the structure in the stimuli. Nothing was explicitly told to this group about the nature of the structure underlying the letter strings. Both groups were given the same learning phase, during which they memorized strings produced by an artificial grammar, and the same testing phase, during which they decided whether novel letter strings were or were not grammatical.

Remarkably, the explicitly instructed group of subjects performed worse than the group given neutral instructions in all aspects of the experiment: They took longer to memorize letter strings during the learning phase, they were worse at discriminating grammatical from non-grammatical strings during the testing phase, and they showed evidence of having induced rules that were not representative of the grammar in use. These results suggest that under these conditions explicit processing of complex materials has a disadvantage relative to implicit processing. Reber (1976) argued that, in this particular task, the explicit instructions actually had an interference effect: Subjects were being encouraged to search for rules that, given the nature and the complexity of the artificial grammar, they were unlikely to find in the surface patterns. In Reber's own words, "The simplest conclusion here seems to be the right one: Looking for rules won't work if you cannot find them" (Reber, 1993, p. 48).

Clearly, there is a difference between simply informing subjects that the stimulus materials have some underlying structure and giving subjects precise information about the nature of that structure. A follow-up study by Reber, Kassin, Lewis, and Cantor (1980) attempted to address this issue directly. Subjects were presented with the actual schematic structure of the artificial grammar (i.e., Figure 1) and were given a seven-minute “course” on how the grammar works to generate letter strings. At the same time, subjects were shown 20 strings produced by the grammar, as was done in the standard artificial grammar learning task. Reber et al. manipulated the time when explicit training was introduced: One group was given the grammar at the beginning of the learning phase, a second group received it halfway through the learning phase, and the third group was given explicit training only after seeing all of the exemplars in the learning phase.

The key finding from this study was that the earlier subjects were given explicit training, the better they performed on the classification test. Reber et al. suggested that providing explicit training at the outset of the learning phase focuses the subjects’ attention on the relevant structural relationships in the letter strings. The explicit training did not teach the full grammar to the subjects, Reber et al. stressed, but rather oriented subjects to the relevant dimensions and relationships in the letter strings.

The critics of the abstractionist view are largely the critics of the unconscious view as well, and for similar reasons. Dulany et al. (1984) argued that subjects’ classification decisions were based on their conscious awareness of the presence or absence of key fragments in the test strings. Thus, subjects never derive any information about the actual grammar but instead develop idiosyncratic, correlated grammars via conscious, analytic processes. Perruchet and Pacteau (1990) made a similar argument, that subjects consciously encode frequently occurring fragments of strings presented in the learning phase and then apply this knowledge during the testing phase. Furthermore, Perruchet and Pacteau argued that the actual learning involved in making grammaticality judgments occurred during the testing phase, not in the learning phase, because at that time subjects are aware of the existence of the grammar while they are making classification decisions. Thus, conscious, fragmentary knowledge is strategically applied in the artificial grammar-learning task.

In addition to these criticisms, perhaps the most influential argument against unconscious learning is theoretical in nature. Suppose that implicit and explicit (unconscious and conscious) processes can be represented as two variables, α and β respectively. Implicit learning is said to have occurred in the absence of conscious awareness. That is, the circumstances for establishing the existence of implicit learning are $\alpha > 0$ and $\beta = 0$. Proving the latter, that $\beta = 0$, is highly problematic. In response to Reber’s (1989) review of implicit learning, Brody (1989) argued that nowhere in the entire body of implicit learning research have the “proper” tests been run to determine whether subjects had any conscious knowledge of the rules or underlying system. That is, no study of implicit learning has ever established that $\beta = 0$.

In their recent critique of implicit learning research, Shanks and St. John (1994) expand upon the idea proposed by Brody (1989) that no study has provided sufficient evidence that implicit learning is unconscious. Specifically, Shanks and St. John pointed out two problems inherent in equating consciousness with verbal report. The first, what they called the “Sensitivity Criterion” is that a test of verbal report may not be sensitive to all of the conscious knowledge the participant has available. For example, how does the experimenter know he has asked the right questions and pressed the subject hard enough? The second problem with equating consciousness with verbal report is the potential violation of the “Information Criterion.” This is the notion that a subject’s task performance may depend on information I, but in the test of awareness the experimenter is mistakenly looking for information I*. Shanks and St. John cite the findings of Perruchet and Pacteau as an example of this discrepancy. In their study, the information needed to complete the task (I) was information about permissible bigrams, while the information requested in a standard verbal report concerns syntactic rules (I*). Ultimately, Shanks and St. John concluded that there has not been sufficient evidence demonstrating the existence of unconscious learning and that dissociable forms of human learning do not exist.

In response to these criticisms, Reber (1993) has argued that establishing $\alpha > 0$ and $\beta = 0$ is not necessary for demonstrating implicit learning. Instead, he suggests the relationship can be stated as a simple inequality, $\alpha > \beta$, for a circumstance where implicit knowledge is at work. In other words, when explicit, conscious knowledge is not sufficient to explain performance on a given task in some domain, then implicit, unconscious knowledge must account for this discrepancy. Reber argued that, "The key to uncovering the cognitive unconscious will be found in measures of mental content held consciously (β) that yield lower estimates when compared to those made of the mental content held outside the purview of consciousness (α)" (Reber, 1993, pp. 8-9). The only ontological stance that will be successful in studying unconscious, implicit mental processes holds that the unconscious is the "default condition", a stance Reber refers to as "the primacy of the implicit" (Reber, 1990, 1993). This position will be expanded upon in the following section describing Reber's evolutionary model of the cognitive unconscious.

The controversies surrounding the issues of "what is learned" and "how it is learned" still remain unresolved. The only conclusion that will be drawn here is that throughout the recent history of research on implicit learning, researchers have consistently made the process-purity assumption, the assumption that a one-to-one mapping between a given task and an underlying cognitive process can exist. Clearly, this dubious assumption is at the root of criticisms arguing that conscious, explicit knowledge is never entirely absent, that you can never get $\beta = 0$.

Reber's Evolutionary Model of the Cognitive Unconscious

Reber's motivation to develop a theory of the cognitive unconscious from an evolutionary perspective stemmed from his desire to place contemporary cognitive science within a solid biological framework (Reber, 1992a, 1992b, 1993). Reber was largely dissatisfied with information processing models of cognition that postulated metaphorical boxes and buffers and with nativistic theories of mind (e.g., Fodor, 1983), such as the proposal of an immensely complex and highly specific language acquisition device (e.g., Chomsky, 1986; Pinker, 1994). According to Reber, these proposals lack biological coherence and ecological validity. Instead, a better proposal would be that distinct types of cognitive functions (implicit and explicit, unconscious and conscious) evolved at different times for different reasons. Reber's evolutionary model of the cognitive unconscious is based on four principles from evolutionary biology. The model is useful in the specific predictions it makes concerning dissociations between implicit and explicit cognitive processes. The principles are as follows:

1. The Principle of Success: Forms that have proven their adaptive value become the foundation for later forms.

2. The Principle of Conservation: Successful forms become fixed and begin to serve as foundations for developing forms– thus their core features are unlikely to be substantially modified over time.

3. The Principle of Stability: Early appearing, successful forms tend to be relatively invariant.

4. The Principle of Commonality: Evolutionarily earlier forms will be displayed across species.

Consciousness, Reber argues, was a relatively late arrival on the evolutionary scene and was preceded by sophisticated cognitive functions that operated automatically without its benefit – that is, unconscious/implicit processes. Since implicit cognitive processes are evolutionarily older, Reber emphasizes what he calls the "primacy of the implicit" (Reber, 1990). What he means is that unconscious, implicit processes are the "default mode" and are the foundation upon which emerging conscious, explicit operations have been laid. Based on this evolutionary model, Reber makes several specific predictions about the properties of implicit processes that differentiate them from explicit processes:

1. Robustness: Implicit processes should remain intact in the face of disorders that affect explicit processes.

2. Commonality: The underlying processes of implicit learning should show cross-species commonality.

3. Age independence: Implicit learning should show few effects of age and developmental level compared with explicit learning.

4. Low variability and IQ independence: Implicit learning should show little or no individual differences and also should show little concordance with measures of "intelligence" assessed by standard psychometric instruments.

The first two predictions will not be discussed at length here. As mentioned earlier, implicit memory appears to be left intact following neurological damage (Warrington & Weiskrantz, 1970); evidence has also been found showing preserved implicit learning in the face of various neurological impairments (Knopman & Nissen, 1987; Knowlton & Squire, 1994, 1996; Nissen & Bullemer, 1987). The prediction that implicit learning processes are present in multiple species is largely philosophical in nature and has been discussed in depth elsewhere (Reber, 1993, 1997b). The third and fourth predictions, however, are specific predictions about individual differences in implicit learning that are relevant to the present study. Surprisingly, only a few studies in the literature have specifically addressed the issue of individual differences in implicit learning.

The first study to investigate the relationships among implicit and explicit learning and IQ was conducted by Reber, Walkenfeld, and Hernstadt (1991). Reber et al. compared performance on the standard artificial grammar learning task with performance on an explicit problem-solving task and four subtests from the Wechsler Adult Intelligence Scale-Revised (WAIS-R). The problem-solving task involved predicting the next item in a sequence of letters. For example, given the sequence ABCBCDCDE__, the next letter would be D, since the sequence is broken into chunks of three, each chunk beginning with the next letter in the alphabet after the letter that initiated the previous chunk (ABC-BCD-CDE-__).

Performance on the implicit and explicit tasks showed the predicted pattern of correlations. The correlation between performance on the explicit problem-solving task and IQ was significant ($r = +.69$, $p < .01$); the correlation between the artificial grammar learning task and IQ was not significant ($r = +.25$, $p > .05$); and the implicit and explicit tasks did not correlate significantly with each other ($r = +.32$, $p > .10$). Reber et al. concluded that these findings supported the proposal that implicit tasks are fundamentally different from explicit tasks and that these differences are best viewed within an evolutionary framework (Reber, 1993).

A similar study by Mayberry, Taylor, and O'Brien-Malone (1995) compared performance on implicit and explicit tasks with IQ in school-aged children, Grades 1-2 and 6-7. Mayberry et al. found that performance on an implicit learning task was not related to IQ (r's = +.02 and +.04 for children in Grades 1-2 and 6-7, respectively), but that performance on an explicit task was (r's = +.37 and +.56). Also, the degree of verbalizable knowledge about the implicit test was not related to performance on the implicit test (r's = +.05 in both groups), while the degree of verbalizable knowledge about the explicit test did correlate with performance on the explicit test (r's = +.47 and +.80). These findings provide support for the earlier conclusions made by Reber et al. (1991) that implicit learning does not co-vary with either explicit learning or traditional psychometric measures of intelligence.

McGeorge, Crawford, and Kelly (1997) replicated and extended the findings of Reber et al. (1991). Subjects in this experiment ranged from age 18 to 77 years, allowing a more thorough investigation of the development of implicit and explicit functions across the life span. Subjects also completed a full-scale measure of IQ (the WAIS-R), and thus a factor analysis could be performed to better determine what components of the IQ score were most related to the implicit and explicit tests.

McGeorge et al. found that while the correlation between performance on the implicit test and overall IQ was not significant (r = +.12), there was a small but significant loading on the Perceptual Organization factor (r = +.19), a factor thought to be associated with general fluid intelligence. In contrast, the explicit test showed strong correlations with overall IQ (r = +.67) and with both the Perceptual Organization and Attention-Concentration factors (r's = +.65 and +.53, respectively). Finally, McGeorge et al. found that while there were no differences in performance on the implicit test with increasing age, performance on the explicit test did decrease with age. Thus, the findings reported by McGeorge et al. replicate and extend those of earlier studies comparing implicit and explicit tests with psychometric intelligence and, additionally, are relevant to Reber's (1993) prediction that implicit cognitive functions will be age independent.

Almost all of the discussions concerning individual differences in implicit learning conclude that they do not exist, and this follows from the theoretical arguments proposed by Reber (1992a, 1992b, 1993, 1997a). However, the empirical studies described above demonstrate only that implicit learning does not co-vary with explicit measures of learning, which is not evidence that individual differences in implicit learning do not exist. Furthermore, finding a relationship between explicit tests and IQ and no relationship between implicit tests and IQ, is a foregone conclusion: Psychometric tests of intelligence are designed to measure the same construct thought to underlie an explicit test, not to measure implicit cognitive processes. None of the studies reviewed earlier have focused specifically on finding variability in performance on an implicit learning task. Indeed, the actual variability among individual performance in implicit tests has largely been ignored in these studies. Only recently has Reber softened his stance concerning the existence of individual differences in implicit learning, noting that the studies by both Reber et al. (1991) and Mayberry et al. (1995) did find some individual variation in success on the implicit task, allowing for the possibility that individual differences in implicit learning do exist (Reber & Allen, 2000). However, these individual differences remain unexplained and have not been the focus of any systematic research effort.

To study individual differences, Reber suggests, "If we are to come to some conclusions about inter-individual differences in implicit learning, we need to examine individual performances on implicit and explicit tasks which use a common metric" (Reber & Allen, 2000, p. 241). The argument here is for a task dissociation: A common metric is needed so that a direct comparison can be made between an implicit task and an explicit task. However, this appears be the same strategy used in Reber et al. (1991), Mayberry et al. (1995), and McGeorge et al. (1997), so there is no reason to believe that yet another comparison between an implicit task and an explicit task will provide any further insights into the nature of individual differences in implicit learning. An alternative approach to measuring individual differences in implicit learning would be to first separate the relative contributions of implicit and explicit processes to performance on a specific task, and then attempt to account for variability in the implicit process with some other measure. Based on this reasoning, a new method for measuring individual differences in implicit learning is proposed and developed in the following section.

Measuring Individual Differences in Implicit Learning

As mentioned earlier, almost all of the research on implicit learning has made the process-purity assumption, the assumption that a one-to-one mapping between a given task and an underlying cognitive process exists. Specifically, the theory of implicit learning originally assumed that learning in an artificial grammar-learning task is unconscious (Reber, 1967, 1969, 1976). Critics of implicit learning then argued that learning in an artificial grammar-learning task is accompanied by conscious awareness (Dulany et al., 1984; Perruchet & Pacteau, 1990). A revised stance, proposed by Reber (1993, 1997a), is that learning in an artificial grammar learning task is largely unconscious, but not entirely so. This revised view dismisses the process-purity assumption, since both conscious and unconscious processes can function in a given task. However, simply observing that there is an inequality between the amount of information available for conscious expression and that available to the unconscious does not provide a means for separating the relative contributions of implicit and explicit processes to performance on a given task.

Over the last decade, Jacoby (1991; Jacoby, Toth, & Yonelinas, 1993) has developed a process dissociation procedure in attempt to solve a similar problem, separating automatic and intentional (controlled) influences in memory. Several assumptions from Jacoby's process dissociation framework can also be applied to the study of implicit and explicit influences on learning. The first critical assumption is the rejection of process-purity: A given task does not have to measure only one underlying process but, instead, may simultaneously engage both implicit and explicit processes to varying degrees. Thus, task dissociations (e.g., comparing classification performance with verbalizable knowledge) do not necessarily reflect process dissociations. Second, the processes driving performance on a given task can work in concert to facilitate performance, in opposition to worsen performance, or may have neutral effects on each other. Borrowing an example from Jacoby (1991), automatic (A) and intentional (I) processes can work together to facilitate memory (A + I) or can act in opposition to interfere with memory (A – I). Third, arranging tasks so that performance in a facilitation paradigm can be compared with performance in an interference paradigm will allow us to look for process dissociations, rather than look for task dissociations. Finally, Jacoby argues that a measure of the implicit, unconscious influences on learning obtained within a process dissociation framework will be less susceptible to the prevailing methodological criticisms in the implicit learning literature, largely concerning task dissociations, and may prove to be insightful about the nature of any possible individual differences in implicit learning.

A recent study by Destrebecqz and Cleeremans (2001) applied the process dissociation procedure to an implicit sequence-learning task, the serial reaction time (SRT) task, developed by Nissen (Nissen & Bullemer, 1987). In a typical SRT task, subjects are presented with a series of sequentially structured stimuli, usually on a row of four lights. On each trial, subjects see a light in one of the four locations "light up" and are asked to press as fast and as accurately as possible a key corresponding to the location of the light. For some subjects, the sequence of lights is generated randomly, while for others the sequence of lights follows a repeating pattern. The typical finding in SRT experiments is that reaction times (RTs) tend to remain constant across trials in the random lights group, while RTs progressively decrease across trials in the repeating pattern group. Furthermore, RTs will increase dramatically if the repeating pattern is abruptly modified. These findings suggest that subjects are able to learn to respond to the repeating pattern of lights, even though subjects fail to demonstrate verbalizable knowledge about the pattern (Nissen & Bullemer, 1987; Willingham, Nissen, & Bullemer, 1989).

Destrebecqz and Cleeremans (2001) examined the contribution of explicit knowledge in an SRT task by using a free generation task and a recognition memory task. After being trained in a standard SRT task, subjects were informed that the stimuli they had seen earlier had actually followed a repeating pattern. Subjects were then asked to freely generate several trials that "resembled the training sequence as much as possible." This generation task was performed under "inclusion" instructions, so that presumably implicit and explicit knowledge bases would act in concert to facilitate performance (E + I). After performing the generation task in the facilitation condition, subjects were asked to freely generate several sequences under "exclusion" instructions – that is, they were told to avoid reproducing the sequential regularities of the original training sequence. In this condition, an implicit knowledge base (if implicit learning had occurred) would interfere with performance on the generation task (E – I). Following both generation tasks, subjects were given a recognition memory task that asked them to decide whether fragments of sequences were part of the original training sequence. Subjects provided a rating, on a six-point scale, of how confident they were that the fragment had occurred in the training sequence.

Destrebecqz and Cleeremans (2001) found that subjects were able to produce some explicit knowledge of the training sequence in the free generation task under inclusion instructions. However, when subjects were asked to deliberately exclude sequential regularities from the training sequence, they were unable to avoid projecting their implicit knowledge in the sequences they generated. In the recognition memory test, subjects were mostly unable to discriminate old and new fragments of the training sequence. Destrebecqz and Cleeremans concluded that in attempting to separate the relative contributions of implicit and explicit processes, their findings provided evidence that sequence learning can be unconscious.

The application of the process dissociation procedure used in the present study is similar to that of Destrebecqz and Cleeremans (2001). The task, however, was designed to better quantify implicit knowledge using a measure that is much more sensitive to variability among individuals. Looking back on the original studies of artificial grammar learning, Miller (1958) and Reber (1967) both showed that subjects were better at memorizing letter strings governed by a grammar than at memorizing random letter strings. One question that was not addressed in these early studies, and has not been addressed since that time, is whether having learned an artificial grammar will improve later memory for strings generated by that same grammar. Simply put: Can implicit knowledge about an artificial grammar improve memory span for sequences governed by that grammar?

A significant early experimental psychology textbook describes memory span as folows: "The concept of span, derived from the span of the hand, conveys the idea of width of grasp. How much can be spanned or grasped at once?" (Woodworth, 1938). Memory span as a dependent measure can be used as an alternative to classification performance and lends itself nicely to the process dissociation procedure. Immediate serial recall is generally accepted as a measure of explicit memory that involves conscious encoding and retrieval of a list of items. The goal of this study was to design a new task where memory span performance, a largely explicit cognitive process, would be facilitated by prior implicitly learned knowledge (E + I). Comparing performance on this task with performance on an equivalent memory span task where there is no help from prior implicitly learned knowledge (E + 0) could then yield a measure of the relative contribution of implicit learning (I).

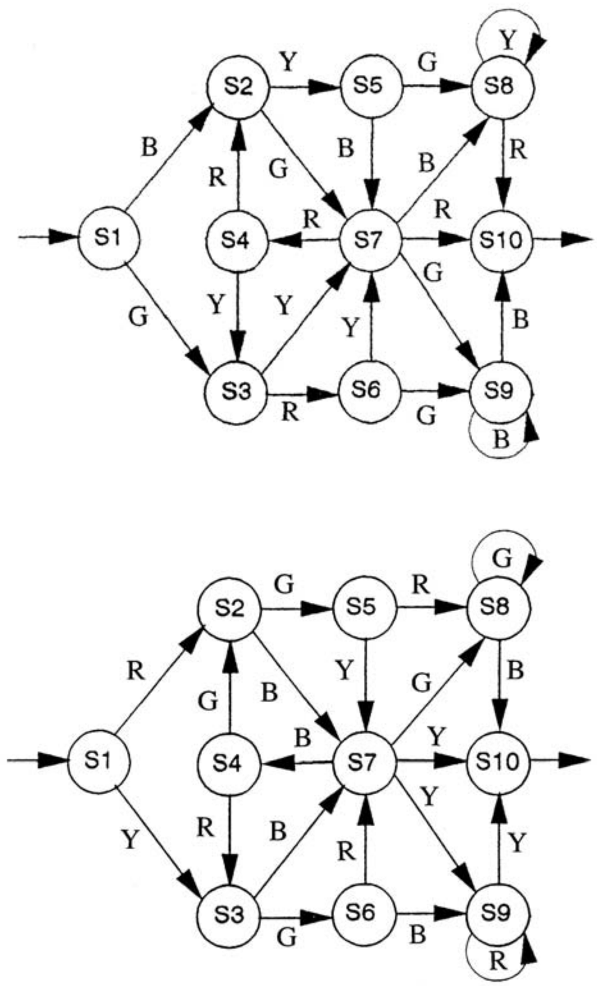

Figure 2. The two artificial grammars used to generate sequences in this experiment, adapted from Brooks & Vokey (1991). The grammars share the same syntax and vocabulary, but differ in their syntax-vocabulary arrangements.

The task used in the present experiment was relatively simple and straightforward. Subjects were presented with a sequence of colors and were asked to immediately reproduce the sequence, using a custom designed response box. Subjects performed this same task during an "acquisition phase" and a "test phase." The sequences presented to the subjects during the acquisition phase were generated by an artificial grammar (see Figure 2). By reproducing sequences during the acquisition phase, subjects were given exposure to the underlying grammar. During the test phase, half of the sequences presented were new sequences that came from the same grammar that the subject had been trained on. The other half of the sequences presented during the test phase were new sequences generated by a different grammar, to which the subject had not been given any prior exposure. Thus, the ability to remember and reproduce sequences that came from the "Trained" grammar would be facilitated by implicitly learned knowledge (Trained = E + I). However, performance on "Not Trained" sequences would not be facilitated by any implicit knowledge (Not Trained = E + 0).

In carrying out this task, however, it is possible that subjects could consciously and explicitly remember sequences that occurred during the acquisition phase and then use that explicit knowledge to improve their memory span during the testing phase. In other words, it is possible that remembering and reproducing sequences from the "Trained" grammar is entirely due to explicit knowledge (Trained = E + E). To account for this possibility, an additional task was included that would place implicit and explicit knowledge bases in opposition.

After completing the acquisition and test phases, subjects were given a recognition memory test that consisted of several types of sequences. "Old" sequences, selected from the first part of the experiment, came from either the "Trained" grammar or the "Not Trained" grammar. Three types of "New" sequences were used: Ones that came from the "Trained" grammar, ones that came from the "Not Trained" grammar, and ones that were randomly generated and did not conform to the rules of either grammar. If subjects had developed an explicit knowledge base during the acquisition phase, then they should be best at discriminating between old and new sequences that came from the Trained grammar (because Recognition = E + E). However, if implicit learning occurred during the acquisition phase of the experiment, then subjects should be worst at discriminating between old and new sequences, because implicit knowledge about the grammar and explicit memory for actual sequences would be set in opposition (Recognition = E – I).

The recognition memory test was also specifically designed to assess subjects' judgments about their phenomenological experience while recognizing grammatical sequences, using a procedure developed by Tulving (1985). During the recognition memory test, subjects were presented with a sequence and asked to judge whether the sequence was "old" or "new". If a sequence was judged old, then subjects were asked to further distinguish between two states of awareness: remembering and knowing. A "remember" experience is defined as one in which the subject can mentally relive the original occurrence of the sequence. A "know" judgment is made when subjects are confident that the sequence had occurred before but are unable to re-experience its occurrence. There is a sizeable literature on remember and know judgments (see Rajaram & Roediger, 1997) providing evidence that remember-know judgments do not simply reflect states of confidence, since several variables can differentially affect remember-know judgments and confidence ratings in these tasks (Rajaram, 1993).

The sequences of colors were presented to subjects using the Simon memory game (see Figure 3), a method of measuring immediate memory span that has been developed in our laboratory (Cleary, Pisoni, & Geers, 2001). In previous research, we have used the memory game to measure immediate serial recall in deaf children with cochlear implants, in normal-hearing children, and in normal-hearing adults (Pisoni & Cleary, 2002). The memory game allows stimuli to be presented to subjects using three different stimulus presentation formats. One group of subjects was presented with visual sequences on the memory game (sequences of colored lights); the second group was presented with auditory sequences (sequences of spoken color words); and the third group was presented with auditory + visual sequences (sequences of colored lights and spoken color words presented simultaneously). After an entire sequence was presented, subjects simply reproduced the pattern by pressing the response buttons on the memory game response box.

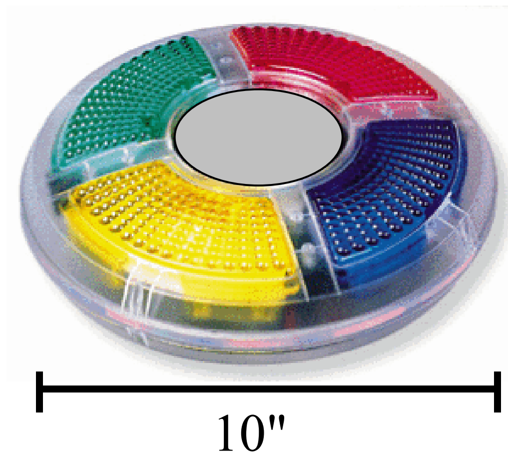

Figure 3. The Simon memory game. Subjects reproduce sequences of colors, presented in auditory, visual, or auditory + visual formats, by pressing the colored response buttons.

The specific predictions in this study were, first, that subjects would have larger memory spans for sequences that came from the grammar they were trained on versus sequences that came from the grammar on which they were not trained. Second, the particular grammar learned by the subject should not make any difference in performance: A comparable learning effect should be found for subjects trained on Grammar A and for subjects trained on Grammar B. Third, subjects should be worse at discriminating old-new sequences from the "Trained" grammar than at discriminating old-new sequences from the "Not Trained" grammar. In other words, subjects should be more likely to falsely recognize, and falsely remember, sequences from the "Trained" grammar, compared with sequences from the "Not Trained" grammar or randomly generated sequences. Such a finding would indicate that implicitly learned knowledge about the "Trained" grammar interfered with the ability to correctly reject a new grammatical sequence. Lastly, individual differences in the size of the learning effect (i.e., variation in the degree of implicit learning) should co-vary with a standard, unrelated explicit measure of immediate memory span, assessed using a traditional digit span task.

It may be helpful to place the current investigation of individual differences in implicit learning within a somewhat larger framework that deals directly with an important clinical problem. The Simon memory game was originally developed as a method of measuring memory span in congenitally deaf children who use cochlear implants, a device that provides access to sound by delivering electrically-coded signals to the auditory nervous system (Miyamoto, 1995). A wide array of individual differences in outcome measures of speech perception and overall language development has been observed in this population of children (Pisoni, Cleary, Geers, & Tobey, 2000; Pisoni, Svirsky, Kirk, & Miyamoto, 1997). At the present time, there is no clear explanation of why some children appear to do well at acquiring language with their cochlear implants while other children do not. A substantial portion of the research in our laboratory has been devoted to investigating the nature of individual differences in the language development of deaf children who use cochlear implants (Cleary, Pisoni, & Geers, 2001; Pisoni, 1999, 2000; Pisoni & Cleary, 2002; Pisoni & Geers, 2000; Pisoni et al., 1997; Pisoni et al., 2000).

A central thesis in this research has been that the operation of higher-level cognitive processes may ultimately be responsible for the variability in language development observed in this population of children. It has been argued elsewhere that immediate memory span and other measures of cognitive processes such as encoding, storage, and retrieval of information form the foundation for language abilities (Gupta & MacWhinney, 1997). However, traditional methods of measuring memory span involve the verbal reproduction of a presented list of items, which could confound results obtained from this population of children, because of articulation problems. Some very young children with cochlear implants have difficulty producing intelligible speech, due to differences in speaking rate and fluency of articulation. Thus, the Simon memory game was developed in order to measure memory span without requiring an explicit verbal response.

While the endeavor to account for individual differences in the language abilities of deaf children with cochlear implants has been successful (Pisoni et al., 2000), none of the experimental techniques in this research program have been developed specifically to measure individual differences in implicit cognitive processes. Indeed, most researchers believe either that individual differences in implicit learning do not exist or that they are not a significant research issue (e.g., Reber, 1997a). Many arguments have been made that the emergence of language abilities is due largely to implicit mechanisms (Gupta & Cohen, in press; Kirsner, 1994; Reber, 1967, 1989, 1993; Winter & Reber, 1994). The argument follows, then, that individual differences in language abilities might be a function of individual differences in underlying implicit processes. Thus, investigating the possibility that individual differences in implicit learning are responsible for some portion of the observed individual differences in language abilities (in any population – but in particular, among deaf children who use cochlear implants) is potentially a highly significant research issue, particularly for a research program interested in understanding the underlying basis of individual differences in order to develop new intervention strategies to improve the language abilities in those children who show relatively poor development (Pisoni et al., 2000).

Method

Subjects

One hundred and twenty Indiana University undergraduates, ages 18 to 24, participated in this study for partial fulfillment of course requirements for introductory psychology. All participants were native speakers of English with no speech or hearing disorders and had normal or corrected-to-normal vision at the time of testing.

Materials

Digit Span. Tokens of the 10 spoken digits ("0" to "9") obtained from the Texas Instruments 46-Word (TI46) Speaker-Dependent Isolated Word Corpus (Texas Instruments, 1991) were used for the auditory digit span task. Auditory stimuli were presented over high-quality headphones at 75 dB SPL. Subjects made their responses by writing in prepared answer booklets at the end of each trial. After recording their responses, subjects initiated the next trial by pressing the "Enter" key on the keyboard.

Simon Memory Game. Auditory tokens of the four color words ("red," "yellow," "green," and "blue") were recorded by one male speaker of American English. The memory game response box was modeled after the commercial product "Simon" by Milton Bradley (see Figure 3), which consists of four colored, back-lit response buttons. Subjects made their responses to auditory, visual, or auditory-plus-visual stimuli by pressing the response buttons on the memory game (Cleary, Pisoni, & Geers, 2001).

Two artificial grammars (referred to as Grammar A and Grammar B) were used to generate grammatical sequences. The grammars were adapted from Brooks and Vokey (1991) and are shown in Figure 2. These particular grammars were chosen because they could generate a greater number of short grammatical sequences than other frequently used grammars (e.g., Figure 1; Reber, 1967). Because Grammar A and Grammar B share the same syntax and the same vocabulary, the sequences they generate should be equally complex and equally difficult to remember and reproduce. Each grammar consists of a vocabulary (the colors “red,” “yellow,” “green,” and “blue,” represented as R, Y, G, and B in the diagram), and a syntax, which is the set of states (represented as circles) and the transitions between those states (represented as arrows). The generation of a grammatical sequence begins by entering the grammar at state S_1. Each transition from any state S_i to any state S_j produces an item in the sequence. The sequence ends when state S_{10} is reached. The sequence of colors produced depends upon the path taken through the state diagram of the grammar.

The number of possible sequences at a given length that each grammar can generate was determined for lengths 4 through 10. Additionally, the number of possible random sequences at each length was determined. These values, shown in Table 2, illustrate how the artificial grammars used in this study function to constrain the number of possible acceptable sequences. For example, at length 7, 30 sequences out of a possible 16,384 random sequences (0.18%) conform to each of the grammars.

Grammatical sequences used in the experiment were selected pseudo-randomly from the set of all possible grammatical sequences from length 4 to length 10. No sequence with more than three consecutive repetitions of a given color was used. Sequences were selected for the acquisition phases so that each branch of the grammar was represented. Sequences were selected for the test phase to ensure that no sequence occurred in both acquisition and testing.

List Length	No. of Grammatical Sequences	No. of Random Sequences
4	8	256
5	10	1024
6	14	4096
7	30	16,384
8	46	65,536
9	58	262,144
10	98	1,048,576

Table 2. The number of possible grammatical sequences that Grammar A and Grammar B can generate at each list length, from length 4 to length 10, compared with the total number of possible random sequences at each length.

An additional set of non-grammatical sequences, lengths 5 through 7, was randomly generated for use in the recognition memory test. All random sequences were checked to ensure that they did not conform to the rules of either grammar. These random sequences were allowed to begin with any of the four colors in the vocabulary. However, an equal number of random sequences beginning with each color was used in the recognition memory test.

Procedure

Subjects were tested in groups of three or fewer in a sound attenuated testing room. All subjects first completed a digit span task. Then they received the acquisition phase, test phase and a final recognition memory test on the Simon reproduction task.

Digit Span. Subjects were presented with a list of digits over headphones. Once the entire list had been presented, subjects wrote down as many digits from the list as they could remember, in the order in which they were originally presented. The lists of digits began at length 4 and increased to length 10, with two lists presented at each length, for a total of 14 trials.

Acquisition Phase. Using the Simon memory game, subjects were presented with a sequence of colors and were simply asked to reproduce the sequence by pressing the response buttons. Color sequences were presented either auditorily (a sequence of spoken color words), visually (a visual-spatial sequence of colored lights), or audiovisually (a visual-spatial sequence of colored lights and the same sequence of spoken color words, presented simultaneously). Stimulus presentation format was a between-subjects factor. Subjects were only exposed to sequences that came from one grammar (A or B). The grammar used during acquisition was counterbalanced across subjects. Sequences began at length 4 and increased to length 10, with two sequences presented at each length, for a total of 14 trials per run. Acquisition consisted of two runs, so that subjects reproduced a total of 28 different sequences generated by one of the two grammars.

Test Phase. Subjects proceeded seamlessly from the acquisition phase into the test phase, without being informed about the existence of the grammar. The task during testing was identical to the task during acquisition: Subjects reproduced test sequences by pressing the response buttons on the Simon memory game. For each subject, the same stimulus presentation format was used in both acquisition and testing. Half of the sequences used during testing were novel sequences that came from the grammar on which the subject had been trained. The other half of the testing sequences came from the grammar on which the subject had not been trained. “Trained” and “Not Trained” sequences were randomly distributed throughout the test phase. Sequences began at length 4 and increased to length 10, with two sequences presented at each length, for a total of 14 trials per run. The test phase consisted of four runs, so that subjects reproduced a total of 28 different sequences from the “Trained” grammar and 28 different sequences from the “Not Trained” grammar.

Recognition Test. After completing the acquisition and test phases, subjects were given instructions about making old-new and remember-know judgments. They were told that they would be given additional sequences on Simon, some of which they had been exposed to earlier during the first part of the experiment. If the sequence had been previously presented, subjects were to indicate “old” by pressing the Green button on Simon. If the sequence had not been previously presented, subjects were to indicate “new” by pressing the Red button on Simon. If a sequence was judged old, subjects were told to further distinguish whether they “remembered” the sequence or whether they “knew” that the sequence was old. Detailed instructions about making remember-know judgments were given, modeled after Rajaram (1993) and Roediger and McDermott (1995). Subjects were told that a “remember” judgment should be made for sequences for which they had a vivid memory of the actual original presentation of that sequence, while a “know” judgment should be made for sequences that they were confident had been presented, but for which they lacked the feeling of remembering the actual occurrence of the sequence. Subjects indicated a “remember” response by pressing the Yellow button on Simon and a “know” response by pressing the Blue button on Simon. To help subjects remember which button corresponded to which response, a card labeling each button with the appropriate response was placed on the Simon response box. Once again, subjects were not informed about the existence of the grammars prior to the recognition memory test.

The recognition test was composed of 50 sequences. Ten “Old Trained” and ten “Old Not Trained” sequences were selected from sequences used during the test phase. Ten “New Trained” and ten “New Not Trained” sequences were generated from each grammar, respectively, and presented as grammatical distracter items. Additionally, ten “New Random” sequences that did not conform to the rules of either grammar were used as distracters. Table 3 illustrates the five conditions used in the recognition memory test. The sequences used in the recognition memory test were of lengths 5 through 7, so that recognition performance would not be confounded by capacity limitations in memory span. Two sequences of length 5, four sequences at length 6, and four sequences at length 7 were used in each condition. The sequences in each condition were randomly distributed throughout the recognition test.

	Trained	Not Trained	Random
Old	10	10	
New	10	10	10

Table 3. Schematic of the distribution of sequences used in the recognition memory task.

After the recognition memory test was completed, subjects answered a set of questions attempting to assess their explicit knowledge of the grammars used to generate the sequences (modeled after Reber, 1989, 1993).

Results

Memory Span

Memory span scores were obtained by adding up the total number of items correctly reproduced on each perfectly recalled trial (an "absolute span score", after LaPointe & Engle, 1990). This scoring method was chosen because it provides a way of combining both list-based and item-based performance into a single composite score.

The mean memory span scores for the digit span task, the acquisition phase, and the test phase are shown in Table 4, listed by presentation modality group (n = 40 in each group). Two scores were obtained during the test phase, one score for sequences from the "Trained" grammar, and one score for sequences from the "Not Trained" grammar. Performance on the digit span task and the acquisition phase were comparable across all three modality groups. During the test phase, memory span scores for sequences that came from the "Trained" grammar were higher than memory span scores for sequences from the "Not Trained" grammar.

A one-way between-subjects ANOVA was performed on the digit span scores. The results revealed no differences among the three presentation modality groups ($F < 1$). The mean scores, ranging from 48.35 to 49.75, are consistent with the findings from other studies carried out in our laboratory that have used the same methods of measuring digit span (Goh & Pisoni, 1998; Karpicke & Pisoni, 2000). An additional one-way between-subjects ANOVA was performed on the acquisition phase scores. The results showed no differences among the three presentation modality groups ($F < 1$), indicating that performance during the acquisition phase was comparable in each presentation modality group.

Presentation Modality	Digit Span	Acquisition Phase	Test Phase: Trained	Test Phase: Not Trained
AV	48.55 (19.75)	68.98 (28.28)	83.65 (26.55)	63.45 (21.04)
AO	49.75 (19.39)	64.38 (25.73)	75.53 (28.28)	60.88 (26.99)
VO	48.35 (19.31)	63.40 (22.94)	70.90 (27.50)	60.65 (20.44)

Table 4. Mean memory span scores (standard deviation in parentheses) obtained from the digit span task, from the acquisition phase, and from the test phase. Performance during the test phase is divided into two span scores, one score for the "Trained" grammar, and one score for the "Not Trained" grammar. The scores are listed by presentation modality, $n = 40$ in each group.

"Sequence type during training" (Trained or Not Trained) was submitted to an ANOVA as a within-subjects factor, with presentation modality group (AV, AO, or VO) and grammar learned during training (A or B) as between-subjects factors. The analysis revealed a main effect of Sequence Type, $F(1, 114) = 73.002$, $p < .0001$, which will be referred to as the "learning effect". The learning effect refers to the finding that during the test phase, memory span for Trained sequences was significantly higher than memory span for Not Trained sequences. The learning effect in the auditory + visual (AV) condition is depicted in Figure 4, illustrating that performance on "Trained" sequences was better than performance on "Not Trained" sequences across almost all list lengths. Moreover, the learning effect did not interact with the grammar learned during training, $F(1, 114) = 2.384$, $p > .10$. This finding indicates that the learning effect was not simply a result of sequences from one grammar being easier to learn and remember than sequences from the other grammar. The interaction between the learning effect and presentation modality was marginal, $F(2, 114) = 2.677$, $p = .07$.

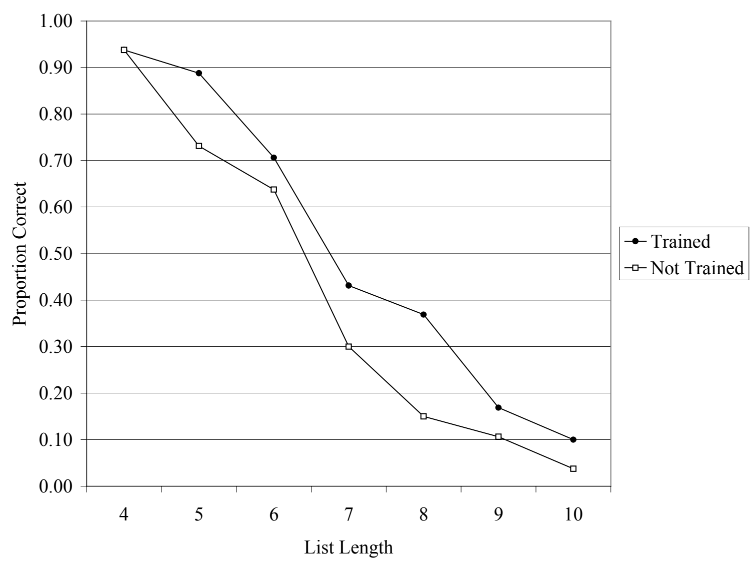

Figure 4. Depiction of the learning effect (memory span for Trained sequences is higher than memory span for Not Trained sequences) in the auditory+visual condition ($n = 40$), showing that performance on Trained sequences is better than performance on Not Trained sequences from list lengths 5 through 10.

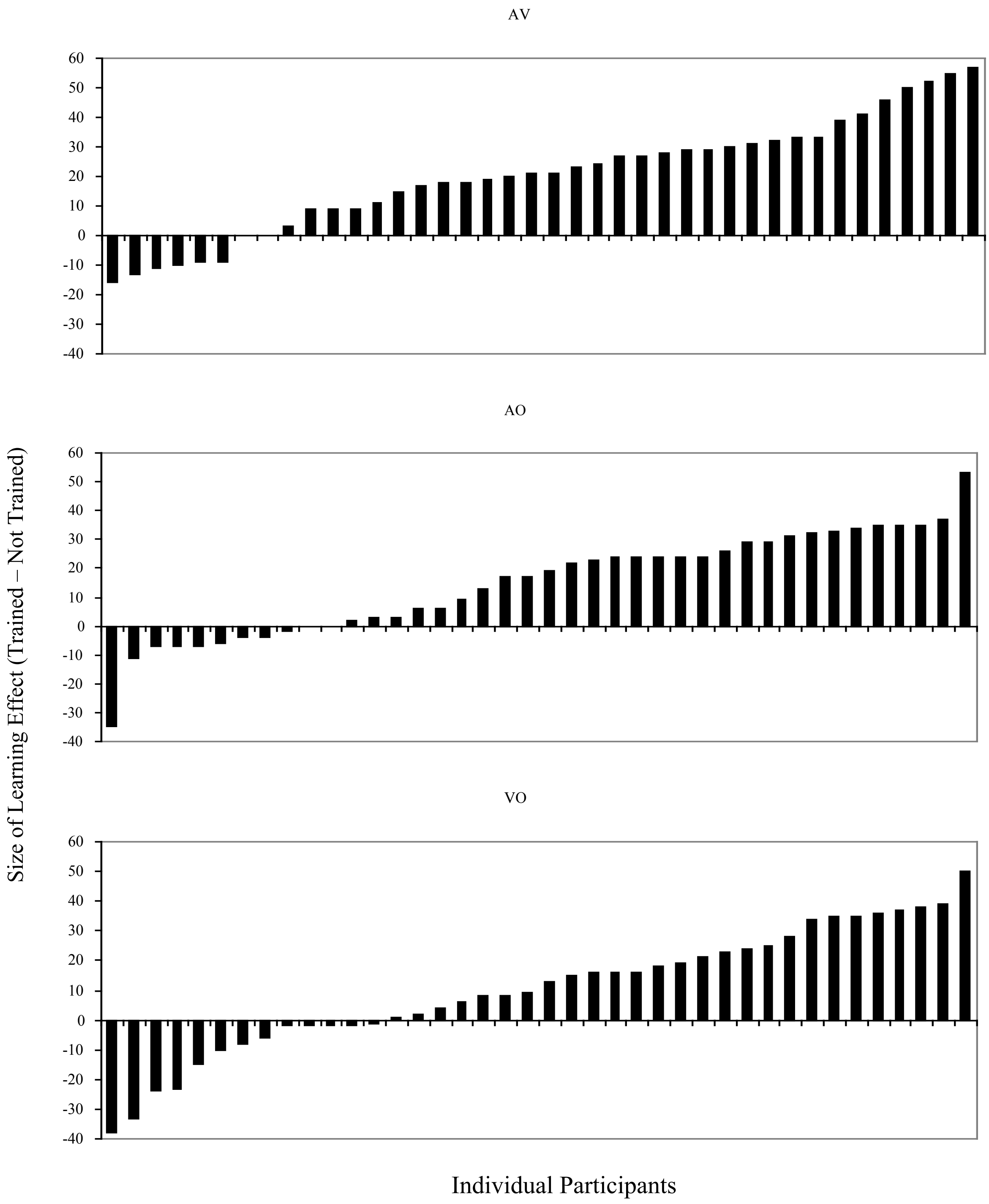

Figure 5. The size of the learning effect (Trained – Not Trained) for each individual participant in each of the three presentation modality conditions, rank ordered from smallest to largest effect. (AV=audiovisual, AO=auditory only, VO=visual only)

The size of the learning effect for each individual participant (i.e., "Trained" memory span score minus their "Not Trained" memory span score) is plotted in Figure 5. While most subjects showed a learning effect (88 out of 120, 73%), some did not, and there was a wide range of variability in the size of the learning effect among subjects across all three modality conditions (ranging from –38 to +57). To investigate some possible sources of this variability, bivariate correlations were performed comparing the size of the learning effect with digit span and with performance during the acquisition phase. Moderate positive correlations, shown in Table 5, were found between digit span and the learning effect, and between acquisition phase score and the learning effect, in both the auditory + visual (AV) and the auditory only (AO) conditions. In the visual only (VO) condition, a weak positive correlation was found between performance during the acquisition phase and the size of the learning effect ($p > .10$). No correlation was found between digit span and the learning effect in the VO condition.

Presentation Modality	Memory Span	Size of Learning Effect (r)
AV	Acquisition Phase	.52**
	Digit Span	.42**
AO	Acquisition Phase	.56**
	Digit Span	.44**
VO	Acquisition Phase	.20
	Digit Span	-.02

Table 5. Correlations of digit span and performance during the acquisition phase with the size of the learning effect. ** indicates $p < .01$.

The finding that performance during the acquisition phase correlated with the size of the learning effect is not entirely surprising, because it was predicted that individuals who performed better while acquiring the grammar would subsequently show a larger learning effect. However, the finding that an unrelated measure of memory span, the digit span task, correlated with the learning effect was more surprising. Figure 6 shows the scatter plots of the relationship between digit span and the size of the learning effect. These plots clearly illustrate that in the AV and AO conditions, individuals with higher auditory digit spans showed a larger learning effect.

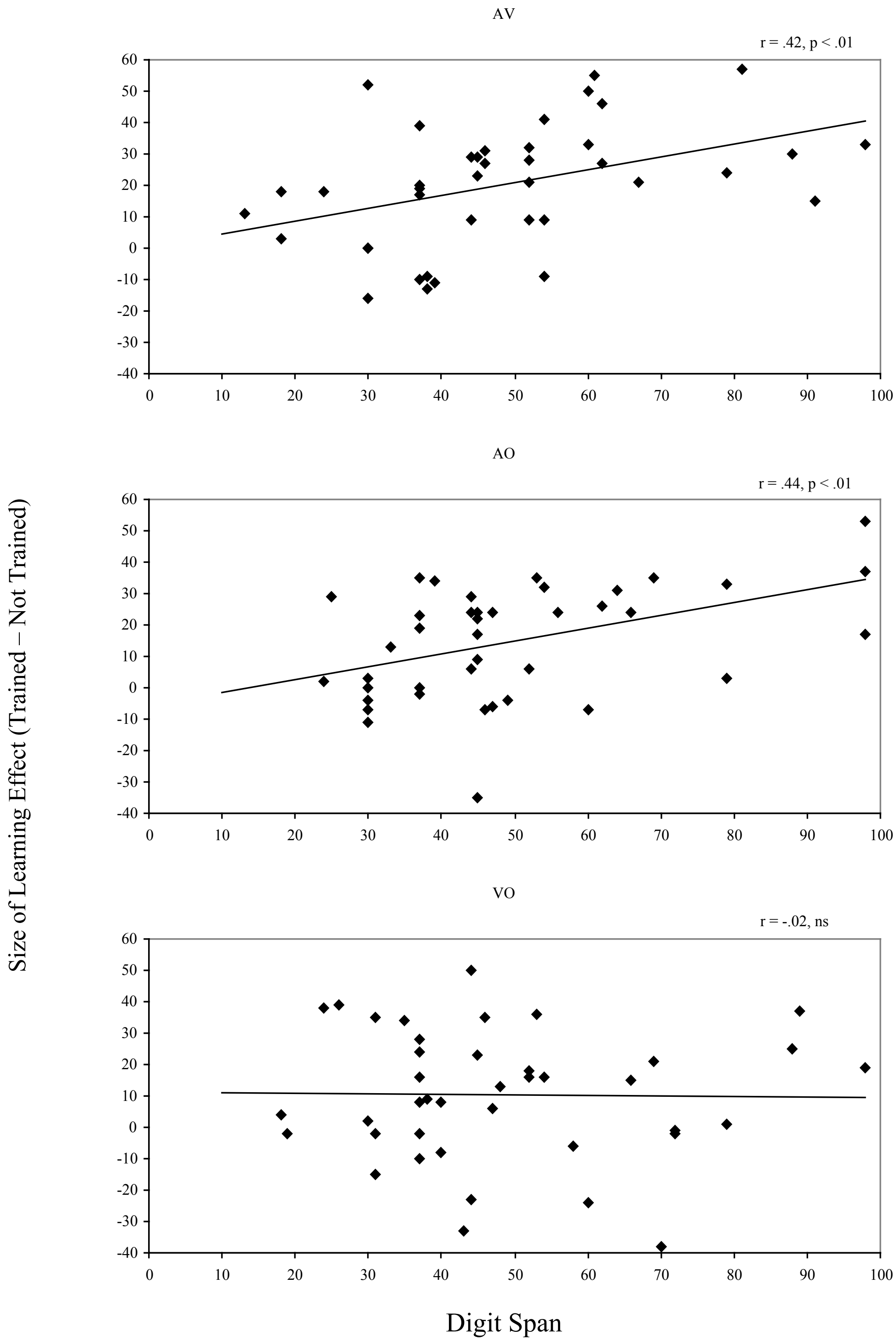

Figure 6. Scatter plots showing the relationship between auditory digit span and the size of the learning effect in each modality condition. (AV=audiovisual, AO=auditory only, VO=visual only)

Recognition Memory

Table 6 shows the probability of calling a sequence "Old" in the recognition memory test for each sequence type (Old Trained, Old Not Trained, New Trained, New Not Trained, and New Random; see Table 3). No differences were found in the pattern of hit rates and false alarm rates in all three presentation modality conditions. Thus, the data from the recognition memory test displayed in Table 6 are collapsed across modality groups. It is immediately evident that there were high false alarm rates for both "Trained" and "Not Trained" sequences, while subjects seemed to be able to correctly reject new random sequences with relative ease.

Sequence Type and Condition	Proportion of Responses Old	R	K
Old			
Trained	.54	.22	.32
Not Trained	.53	.20	.33
New			
Trained	.52	.23	.29
Not Trained	.47	.15	.32
Random	.28	.09	.19

Table 6. The probability of calling a sequence "Old" in the recognition memory test, collapsed across modality groups. R indicates "Remember" responses, K indicates "Know" responses.

To determine the relative discriminability of sequences from the "Trained" grammar and sequences from the "Not Trained" grammar, a measure of *d*' was obtained for the Trained and Not Trained conditions. Six subjects (out of 120 total) who performed either at floor or at ceiling in at least one of the recognition memory test conditions were excluded from the signal detection analysis. The mean *d*' for "Trained" sequences was 0.02, while the mean *d*' for "Not Trained" sequences was 0.18. Both of these numbers are very low, indicating an overall difficulty in discriminating old and new sequences generated by either grammar. Nevertheless, *d*' for "Not Trained" sequences was significantly higher than *d*' for "Trained" sequences, $t(113) = 2.414$, $p < .01$, indicating that subjects were worse at discriminating between old and new sequences generated by the grammar they were exposed to during acquisition.

Additional analyses of remember-know judgments made during the recognition memory test (see column two in Table 6) revealed a compelling false memory effect. The probability of saying "remember" to a sequence generated by the grammar on which the subject was "Not Trained" was significantly lower for new sequences than for old sequences, $t(119) = 2.873$, $p < .01$. However, the probability of saying "remember" to sequences generated by the "Trained" grammar was not different for old and new sequences, $t(119) = .396$, ns. This finding indicates that subjects falsely remembered sequences that had never been presented before, but which were generated by the grammar on which they had been trained, at about the same level as they correctly remembered sequences that had actually been presented previously.

Discussion

The primary findings from this study can be summarized as follows. First, a learning effect was found. Memory span for sequences generated by an artificial grammar to which subjects had been previously exposed was significantly higher than memory span for sequences generated by a different grammar that subjects had not been exposed to during the acquisition phase. This learning effect was found under three presentation conditions: auditory + visual (AV), auditory only (AO), and visual only (VO). Furthermore, the learning effect was not merely the result of one particular grammar generating sequences that were easier to memorize than those generated by the other grammar: Training on either grammar produced an equivalent subsequent learning effect in terms of increases in immediate memory capacity in the test phase.

Second, a wide range of variability in the size of the learning effect was found among individual subjects. Most subjects showed evidence of having benefited from prior exposure to one of the artificial grammars, but a few failed to show any benefit. Correlation analyses revealed that subjects who performed better during the initial acquisition phase, in which they were exposed to one of the artificial grammars, showed a larger learning effect during the test phase than subjects who performed more poorly. Furthermore, in the AV and AO conditions, significant correlations were found between performance on the digit span task, an unrelated measure of memory span capacity, and the size of the observed learning effect. This finding suggests that individuals with larger immediate memory span capacity are better able to acquire knowledge about the higher-order sequential dependencies underlying the structure of an artificial grammar and subsequently use their knowledge about the deep structure of the grammar to improve their memory span for new sequences that follow that particular set of grammatical constraints.

Finally, the recognition memory test revealed that subjects demonstrated learning effects without having the ability to display explicit knowledge about grammatical sequences. Although subjects were largely unable to discriminate between old and new sequences that had been generated by either grammar, subjects showed significantly better discrimination for sequences from the "Not Trained" grammar than for sequences from the "Trained" grammar. This finding indicates that implicitly learned knowledge about the grammar interfered with subjects' ability to discriminate between old and new sequences generated by the grammar on which they had been trained. In addition, remember-know judgments obtained during the recognition memory test provided converging evidence about the subjects' phenomenological experience of recollection. For sequences generated by the "Trained" grammar, the proportion of "remember" responses was essentially equivalent for old and new sequences. In other words, subjects claimed to have vivid memories for sequences that were generated by the system of grammatical rules on which they had been trained, but had never actually occurred anywhere previously during the course of the experiment.

The Process Dissociation Procedure Revisited

The primary motivation behind this study was to develop an experimental method of measuring implicit learning, based on the logic of the process dissociation procedure, that would be more sensitive to individual differences than standard implicit learning tasks. The critical assumption of the process dissociation procedure is that a given task is not a pure measure of a single underlying process (Jacoby, 1991). Instead of equating a task with a process, a better method for determining the relative contribution of distinct processes (e.g., automatic vs. intentional, unconscious vs. conscious, implicit vs. explicit) to performance on a given task is to design two paradigms, one in which the underlying processes work in concert to facilitate performance, and another in which the underlying processes work in opposition to interfere with performance.

In the present study, prior exposure to sequences generated by an artificial grammar facilitated subjects' ability to reproduce new sequences generated by the same grammar in an immediate memory span task. The pattern of results obtained suggests that implicit learning of the higher-order sequential dependencies that compose the artificial grammar was responsible for this facilitation in performance. If improved performance had been the result of some form of explicit knowledge about sequences generated by the artificial grammar, then such explicit knowledge should have also facilitated performance in an explicit recognition memory test. However, performance in the recognition memory test as indexed by *d*' was lowest for sequences generated by the grammar to which subjects had been initially exposed, suggesting that implicitly learned knowledge about the underlying structural regularities of the grammar acted in opposition with explicit knowledge to interfere with recognition performance.

The purpose of the present study was not to invent an "implicit learning task." In fact, the argument presented here is that there is no such thing as an implicit learning task. Instead, this study has explored one possible method of measuring the implicit influences on a largely explicit task, involving immediate memory span. The demonstration that two knowledge sources, one implicit and the other explicit, can act either in concert to facilitate performance or in opposition to interfere with performance provides strong support for a process dissociation without relying on a task dissociation. Implicitly learned knowledge selectively improved memory span performance (E+I) and at the same time selectively interfered with recognition memory performance (E–I). Using this procedure, the relative contribution of implicitly learned knowledge to memory span performance was determined for each individual subject and used to explore variation in performance on these tasks. This index of implicit learning revealed a wide range of individual differences not found in previous investigations of implicit learning, which have equated performance on the standard artificial grammar learning task with the degree of implicit learning (Mayberry et al., 1995; McGeorge et al., 1997; Reber et al., 1991). The present investigation differs from these earlier studies in that the primary measure of implicit learning was based on peak immediate memory span, where large individual differences are typically observed.

Relating Capacity and Sequential Learning

The present findings provide a serious challenge to any theory of human cognition that simply writes off individual differences in implicit cognitive processes as non-existent (e.g., Reber, 1993, 1997a). This study has provided new empirical evidence that implicit learning can vary greatly among individuals. When implicit learning is measured not by performance on a given task but, rather, as a process that makes some relative contribution (either positive or negative) to task performance, the variability in implicit learning among individuals is revealed. In addition to this empirical evidence, there are sound theoretical reasons for arguing that individual differences in implicit learning might be responsible in part for individual differences in other cognitive abilities as well. For example, if the mechanism of implicit learning is a substrate for language abilities, then one would expect to find substantial co-variation among a large range of language measures as well as among measures of implicit learning.

The nature of individual differences in implicit learning is not well understood at this time and will require more extensive investigation. The findings in the present study, however, suggest that a relationship exists between memory span capacity and the ability to learn and to use higher-order sequential dependencies. At least one model, proposed by Elman (1993), has also suggested a relationship between memory capacity and the mechanisms of sequential learning. In his study, Elman (1993) constructed a "semi-realistic" artificial language and then attempted to train a simple recurrent network to process sentences from this language. A simple recurrent network is a special type of artificial neural network that employs a "context layer," which is essentially a feedback mechanism, to provide the network with additional input about its own prior internal states (see also Elman, 1990). This recurrent property of the network renders it capable of processing sequential input and learning sequential dependencies by allowing it to encode information about context. In Elman's model, memory capacity was represented by the access the network had to its own prior internal states via the recurrent connections. In order to simulate the maturational development of memory span during childhood, Elman created a network that began with a limited memory capacity that gradually increased by having greater access to the recurrent connections. Elman found that these conditions were optimal for the neural network to learn the "long-distance dependencies" of the artificial language. Elman argued that there is a direct relationship between the gradual increase in memory capacity during childhood and the ability to learn and process sequential information.

The suggestion made in Elman's (1993) simple recurrent network model is that a system with a small memory capacity first learns "shorter-distance" dependencies in a language. As capacity increases, the network becomes able to process "longer-distance" (i.e., "higher-order") sequential dependencies by building upon its prior knowledge about shorter-distance dependencies. Based on these results, Elman (1993) proposed a direct relationship between memory capacity and sequential learning, that the ability to learn higher-order sequential dependencies is a function of the size of memory capacity.

Future Directions

Future studies using immediate memory span to measure implicit learning should be able to address a wide variety of issues. To investigate the representational form of implicitly learned knowledge, a cross-modal transfer study could be carried out using the process dissociation procedure. As mentioned earlier, Altmann et al. (1995) and Manza and Reber (1997) have shown that implicit knowledge acquired in an artificial grammar learning task can be transferred across sensory modalities. An extension of their findings would be to investigate whether exposure to a grammar in one modality (auditory or visual) would transfer over and improve immediate memory span for grammatical sequences presented to the other modality. Finding that the acquisition of implicit knowledge in one modality can be applied to improve memory span for information in another modality would provide further support for abstractionist views of cognition which argue that implicitly learned knowledge is not bound to the physical form of the stimulus but is a representation of higher-order dependencies.

While we showed that individual differences in implicit learning are related to memory span capacity, we did not investigate any possible relationships between implicit learning and individual differences in working memory capacity or executive attention (Engle, 2001, 2002). Working memory capacity is thought to be a system for keeping goal-relevant information active in memory. This construct has been shown to be functionally distinct from traditional views of short-term memory, in that working memory capacity is essentially short-term memory plus controlled attention (Engle, Tuholski, Laughlin, & Conway, 1999; Kail & Hall, 2001). Measures of working memory capacity, such as the operation span, are thought to measure a different cognitive ability than measures of short-term memory capacity, such as the digit span. An investigation of the relationship between working memory and implicit learning using measures of immediate memory span could better clarify the role of attention, the ability to maintain goal-relevant information in an active state, in learning sequential dependencies.

Another important direction for future work would be to investigate relationships between implicit learning and individual differences in language abilities. If the mechanisms of implicit learning are fundamental for language learning, then direct comparisons between implicit learning and any measures of language abilities would clarify this relationship. Among both adults and children, there is a wide range of variability in measures of language processing. Such measures include word recognition, vocabulary knowledge, reading, language comprehension, speaking rate, speech production, second language learning, and "metalinguistic" skills (i.e., what you know that you know about a language). Though implicit learning may be responsible for the observed individual differences in several measures of language processing abilities, no research program has focused specifically on exploring these possible relationships.

Language is an example of a behavior that is retained over a long period of time. Few studies in the implicit learning literature have investigated the long-term retention of implicit knowledge. In one study, Allen and Reber (1980) recruited subjects who had participated in an artificial grammar learning study two years prior (Reber & Allen, 1978) to assess what they had retained from their earlier grammar learning experience. Allen and Reber (1980) found that even two years after learning an artificial grammar, subjects could still correctly classify grammatical and non-grammatical letter strings without having to "re-learn" the grammar. A similar experiment, conducted using the process dissociation procedure, could investigate how well implicit learning is retained over time, whether individual differences in implicit learning can gradually change, and perhaps even whether there is some means of improving an individual's ability to implicitly acquire knowledge about a complex environment.

One of the predictions derived from Reber's (1992a,b, 1993) model of the cognitive unconscious is that implicit learning should be relatively age-independent, compared with explicit cognitive processes. However, this prediction was made based on empirical evidence from the body of knowledge about implicit learning at the time. The process dissociation procedure applied in the present experiment, using immediate memory span to measure implicit learning, proved to be more sensitive to individual differences than the methodology used in standard artificial grammar learning studies. Thus, using immediate memory span as a measure of implicit learning might also be more sensitive to variation across different age groups and different developmental levels. Individual differences in implicit learning might be related to some of the language difficulties experienced by children, such as language delays, for example. In addition, individual differences in implicit learning might account for some portion of the well-documented age-related declines found in a wide range of various cognitive abilities (e.g., Salthouse, 1996).

Finally, the present study has some direct and immediate implications concerning an important clinical problem currently being investigated in our laboratory on the nature of individual differences in deaf children with cochlear implants. As mentioned earlier, there is a wide range of individual differences in outcome on measures of language abilities in this population of children, without any clear explanation of why some children do very well at acquiring language with their implants while others do not (Pisoni & Cleary, 2002). Research in our laboratory has investigated whether individual differences in memory span capacity can account for some portion of the variance in such language measures (Cleary, Pisoni, & Geers, 2001). The present study provides evidence for a direct relationship between memory span capacity and implicit learning, and provides converging evidence supporting the proposal that implicit learning might be a critical mechanism for language learning (see also Winter & Reber, 1994). The new method of measuring implicit learning developed in this study proved to be more sensitive to individual differences than other traditional measures, such as the standard artificial grammar learning task. Perhaps differences in fundamental abilities, such as the ability to learn and to exploit higher-order sequential dependencies in any of various complex stimulus environments, can help explain why some children acquire language very well with their cochlear implants while others do not. Investigation of the possible relationships between implicit learning and individual differences in language abilities in deaf children with cochlear implants could have a wide range of implications, from possibly explaining some of the observed variability in language development, to potentially predicting an individual child's outcome before implantation, and to assessing the benefits of new intervention methods.

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