Transfer and Complexity in Artificial Grammar Learning

Rebecca L. Gomez

New Mexico State University, Las Cruces

Implicit and explicit learning are sensitive to various degrees of complexity and abstractness, ranging from knowledge of first-order dependencies and specific surface structure to second-order dependencies and transfer. Three experiments addressed whether implicit learning is sensitive to this entire range of information or whether explicit knowledge becomes an important factor in cases of more complex learning. Experiment 1 used recognition and prediction to assess deliberate access to knowledge of letter patterns in an artificial grammar learning paradigm. Experiment 2 manipulated stimulus presentation and response in a sequence-based grammar learning paradigm. Learning can occur without awareness in cases of lesser complexity (such as learning first-order dependencies). However, more complex learning, such as that involved in learning second-order dependencies or in transfer to stimuli with the same underlying syntax but new surface features is linked to explicit knowledge. In contrast to Experiments 1 and 2 which assessed deliberate access to knowledge of the acquisition stimuli, Experiment 3 assessed deliberate access to knowledge of the transfer stimuli. Knowledge of initial trigrams in the transfer stimuli appears to play an important role in transfer. These findings are evaluated in terms of postulated implicit learning mechanisms.

The distinction between explicit and implicit learning is important for understanding how people acquire knowledge. Explicit learning is characterized as an active, voluntary, and purposeful process; one in which people generate and test hypotheses in order to adapt to changes in the environment. Such learning is accompanied by a high degree of awareness. Implicit learning, on the other hand, is characterized as a passive, involuntary process, one in which people ‘‘soak-up’’ complex, novel information with little or no awareness of the underlying structure or abstract rules (Reber, 1967; see Reber, 1989, and Seger, 1994a, for reviews).

Two paradigms used extensively in implicit learning research are artificial...
grammars learning and Serial Reaction Time (SRT) learning. In artificial grammar learning, participants are exposed to consonant sequences generated according to a finite state system (see Fig. 1) and are later given a surprise grammaticality test on which they are asked to distinguish valid from invalid instances of the grammar. Learning is evidenced when accuracy on the grammaticality test exceeds that of chance or control performance. In SRT learning experiments, participants learn to track the location of a target in a choice reaction time task. However, unknown to the participants, the location of the target is determined by a repeating sequence. In this case, learning is evidenced by the disparity in reaction times for responding to the repeating sequence as compared to responding to a random sequence. In both experimental paradigms, participants become increasingly sensitive to new information even though they exhibit little verbalizable knowledge.

Implicit learning is thought to be sensitive to the co-occurrence of cues in the environment (Lewicki, 1986), first-order dependencies in sequence structure (e.g., Cohen, Ivry, & Keele, 1990; Frensch, Buchner, & Lin, 1994; Nissen & Bullemer, 1987), higher-order dependencies in sequence structure, i.e., those that depend on knowing two or more preceding items in sequence (Cleeremans & McClelland, 1991; Cohen et al., 1990; Curran & Keele, 1993; Frensch et al., 1994; Reed & Johnson, 1994; Schvaneveldt & Gomez, 1996), transfer to stimuli with corresponding syntax, but new surface features (Brooks & Vokey, 1991; Gomez & Schvaneveldt, 1994; Knowlton & Squire, 1996; Mathews, Buss, Stanley, Blanchard-Fields, Cho, & Druhan, 1989; A. S. Reber, 1969; Whittlesea & Dorkin, 1993), and transfer across sensory modalities (Altmann, Dienes, & Goode, 1995). Transfer performance is commonly taken as the most compelling demonstration of the abstract and complex nature of implicit learning. Performance on implicit learning tests also appears to be preserved in amnesia despite the fact that performance on declarative knowledge tests is not preserved to the same degree (Knowlton, Ramus, & Squire, 1992; Knowlton & Squire, 1994, 1996; Nissen & Bullemer, 1987; Reber & Squire, 1994). Such findings have been interpreted to mean that there are independent implicit and explicit learning systems.
HOW IMPLICIT IS IMPLICIT LEARNING?

It is generally accepted that some form of implicit learning occurs (see Seger, 1994b for an argument for multiple forms of implicit learning); however, there is a great deal of controversy over the nature and limits of such learning. One source of controversy stems from ambiguous usage of the term implicit (Perruchet & Pacteau, 1991) and related controversy over determining appropriate implicit and explicit tests. In some cases “implicit” refers to nonintentional, or incidental, learning. In other cases, implicit refers to unconscious knowledge in memory resulting from the learning process. Such knowledge can affect performance, but is not directly available to awareness by means of deliberate access to memory.

With regard to the first interpretation of the term implicit, there is substantial evidence that acquisition occurs under a variety of incidental conditions. Such conditions include observation (Reber & Allen, 1978; Seger, 1994b), typing (Gomez & Schvaneveldt, 1994; Seger, 1994b), memorization to criterion (Reber, 1969), rating sequences for preference (McAndrews & Moscovitch, 1985), and locating a briefly presented letter string in a set of target letter strings (Mathews et al., 1989). With regard to the second interpretation of the term implicit, a growing body of evidence suggests that much of what is learned is subsequently available to awareness (Dienes, Broadbent, & Berry, 1991; Dulany, Carlson, & Dewey, 1984; Mathews et al., 1989; Perruchet & Amorim, 1992; Perruchet & Pacteau, 1990). For instance, Dulany et al. (1984) instructed participants to cross out the portions of letter sequences making them ungrammatical and underline the portions of letter sequences making them grammatical. The underscored subsequences were then treated as positional rules for simulating grammaticality performance. Because the results of this analysis showed a predictive relationship between positional rules and grammaticality judgments, Dulany et al. concluded that the primary mechanism underlying grammaticality performance must involve deliberate access to knowledge of letter patterns (rather than implicit access to abstract rules). Additionally, Mathews et al., (1989) used a recall procedure, in which participants periodically reported the rules they were using. The results showed substantial access to knowledge of salient letter patterns. Participants were able to communicate rules both specific and non-specific to a particular letter set. The rules were then used by yoked participants to discriminate grammatical from nongrammatical letter sequences. It should be noted that yoked judgments were slightly less accurate than those obtained from the original participants suggesting that verbalizable knowledge may account for some, but not all of grammaticality performance.

It is the latter interpretation of the term implicit that is of interest in the present studies, an assessment of which is crucial for understanding the processes involved in grammaticality performance. According to one view, knowledge of letter patterns is accessed via deliberate memory search. The
activated letter patterns are then matched against the target string in various ways when making grammaticality judgments (e.g., Mathews et al., 1989; Redington & Chater, 1996). According to a second view, implicit processing of a stimulus results in feelings of familiarity (Servan-Schreiber & Anderson, 1990) or degree of success (Dienes, Altmann, & Gao). On this view, grammatical sequences either result in greater familiarity or are processed more successfully than nongrammatical sequences. In distinguishing these views it is important to note that the first emphasizes the active use of knowledge (accessed as a result of deliberate memory search), whereas, the latter view emphasizes implicit processing differences. Distinguishing between these views is important for understanding how artificial grammar learning fits into the larger body of existing memory research (Buchner, 1994). Furthermore, the first view is consistent with evidence for a single memory system, whereas the latter view is consistent with evidence for an independent implicit learning system.

**HOW COMPLEX IS IMPLICIT LEARNING?**

Another source of controversy involves ascertaining the complexity of implicit learning. Rather than being complex or abstract, Perruchet and colleagues (Perruchet & Amorim, 1992; Perruchet, Gallego, & Savy, 1990; Perruchet & Pacteau, 1990) argue that implicit learning results from knowledge of simple event frequencies and co-occurrences. For instance, in a study conducted by Lewicki, Hill, and Bizot (1988), participants tracked the location of a target determined pseudo-randomly on some trials and by rules on other trials. Over time participants responded more rapidly to the rule-based trials than to pseudo-random trials but had no verbal knowledge of the rules. Lewicki et al. interpreted the lack of verbal knowledge to mean participants were engaging in nonconscious rule abstraction. In replicating this study, however, Perruchet, et al. (1990) demonstrated that participants were responding more slowly to pseudo-random transitions because these were more infrequent than were the rule-based transitions, thus implying that implicit learning might better be explained by sensitivity to simple frequency than by learning complex rules.

Similarly, Perruchet and Pacteau (1990) argued that, rather than being based on abstract rules, grammaticality performance might result from explicit knowledge of the first-order dependencies (or pairwise associations) in an artificial grammar. In support of this hypothesis, Perruchet and Pacteau showed that participants trained only on legal letter associations performed no differently on grammaticality judgments than participants trained on whole letter sequences. Furthermore, participants’ ratings of the legality of letter associations were sufficient for modeling performance in the grammaticality task as long as violations did not extend to illegal letter positions.

Perruchet and Pacteau’s (1990) findings provide compelling evidence for how sensitivity to fairly simple information can account for grammaticality
performance in the same letter set, but how would such knowledge factor into transfer performance? Gomez and Schvaneveldt (1994) compared participants trained on legal letter associations to those trained on letter sequences in order to determine whether transfer would result from knowledge of first-order dependencies. Learning on sequences resulted in learning of first-order dependencies, second-order dependencies, and transfer to a changed letter set. In contrast, learning on legal letter associations resulted in learning of first-order dependencies only.

Transfer performance is commonly interpreted as evidence for abstraction and complexity in implicit learning (e.g., Knowlton & Squire, 1996; Mathews, 1990). Presumably, if participants can transfer from specific learning instances to novel instances at test, then the knowledge underlying such performance must be represented in an abstract, generalizable form. Such a position makes sense intuitively, but practically speaking, little is known about the precise details of the mechanisms underlying transfer. For instance, there is substantial evidence for learning of high frequency chunks during acquisition, (Knowlton & Squire, 1994, 1996; Servan-Schreiber & Anderson, 1990) in contrast to whole sequences (Brooks & Vokey, 1991; Vokey & Brooks, 1992), but little is known about how these chunks are used in transfer, other than the fact that knowledge of grammatical bigrams is an insufficient basis for transfer (Gomez & Schvaneveldt, 1994; see also Manza & Reber, 1996).

One proposal for explaining transfer is that abstract knowledge might take the form of rules not specifically tied to the surface structure of the letters, but representing the locations of characteristic patterns such as repetitions or alternations (e.g., Knowlton & Squire, 1996; Mathews et al., 1989). Another proposal is that transfer does not necessarily imply knowledge of abstract rules, but may instead be “abstractable” from specific knowledge at test (Redington & Chater, 1996). However, little is known about access to specific knowledge during transfer. Participants could acquire specific knowledge of chunks during acquisition, but knowledge of the transfer set might not be specific. Alternately, the mapping between acquisition and transfer letter sets could result in specific knowledge of chunks in the transfer set. Recently, Knowlton and Squire (1996) demonstrated transfer with a group of amnesic patients suggesting that access to declarative knowledge is not implicated in transfer. However, there is still a great deal to be learned about mechanisms of transfer in determining exactly how such results generalize to normal learners.

RATIONALE FOR THE PRESENT STUDIES

The present studies are based on the premise that learning and memory mechanisms involved in implicit learning may be sensitive to various degrees of complexity and abstractness, ranging from (a) first-order dependencies and (b) specific surface knowledge to (c) second-order dependencies and (d) abstract knowledge. In the present studies, specific knowledge refers to
knowledge of surface structure (e.g., legal bigrams and trigrams). In contrast, abstract knowledge is defined as knowledge instantiated independently of the specific surface structure acquired during training. With regard to complexity, first-order dependencies (in which the second element in sequence is completely determined by the preceding element) should be easier to learn than second-order dependencies (in which the third element in sequence is determined by the preceding two elements). Transfer to a changed letter set should be even more complex because it should require additional operations (such as use of abstract rules, computation of an implicit mapping, or computation of an explicit mapping based on knowledge of surface structure). Thus, an important question is whether implicit learning is sensitive to the entire range of complexity or whether explicit knowledge becomes an important factor in cases of more complex learning. That is, does implicit learning occur only in simple cases involving first-order dependencies and specific surface structure or does explicit learning play an increasingly important role in more complex cases, such as those involving learning of second-order dependencies and transfer?

The task of identifying the relative contributions of implicit and explicit knowledge to learning is fraught with difficulty. Cleeremans (1993) argues that the issue of determining awareness is empirically intractable and thus should be replaced by more productive questions, such as those pertaining to the mechanisms involved in performance. However, if it can be shown that deliberate access to knowledge of letter patterns is more highly implicated under certain learning conditions than under others (or under certain conditions of complexity), then surely such information contributes to our understanding of the mechanisms involved in learning. For instance, if learning of first-order dependencies occurs even when participants exhibit poor deliberate access to memory (as measured by performance on explicit knowledge tasks), but transfer to changed surface structure occurs only when participants exhibit high performance on explicit knowledge tests, then these findings might suggest variations in the architectures used for modeling learning of first-order dependencies as opposed to transfer. This approach is correlational in nature and as such cannot attest to the causal role of explicit learning, however addressing such issues should help in clarifying implicit learning theory and should reveal more about the relationship between implicit and explicit learning mechanisms.

MECHANISMS OF LEARNING

Two classes of implicit learning models have been posited in the literature. One class of mechanisms predicts memory search for specific features of learning sequences (such as bigrams or trigrams) which are then used in making grammaticality judgments (Druhan & Mathews, 1989; Redington & Chater, 1996; Roussel, Mathews, & Druhan, 1990). The other class of models predicts implicit processing differences for grammatical and nongrammatical
sequences (Cleeremans, 1993; Cleeremans & McClelland, 1991; Dienes et al., 1995; Servan-Schreiber & Anderson, 1990). Models differ in terms of whether they predict learning of specific features or whether structure is encoded at a more abstract level, and in terms of whether transfer performance results from abstract knowledge (Dienes et al., 1995) or is abstracted from specific knowledge at test (Redington & Chater, 1996). Models also differ in terms of whether they predict learning based on the most frequent letter patterns (Dienes et al., 1992; Servan-Schreiber & Anderson, 1990), the most salient patterns (e.g., repetitions, alternations, beginning trigrams, etc.), or both (Druhan & Mathews, 1989).

Table 1 summarizes the predictions made by five computational models of artificial grammar learning. One set of predictions involves the complexity of learning, where learning first-order dependencies represents learning of simple, specific information, and learning of second-order dependencies and transfer represent increasingly more complex learning. Another set of predictions involves characteristics of the learning such as whether knowledge is frequency or salience based, whether knowledge is stored in a specific or abstract form, and whether the primary basis for judgments derives from deliberate memory search and subsequent application of knowledge or directly from implicit processing differences.

### Competitive Chunking

In an early view of artificial grammar learning, Servan-Schreiber and Anderson (1990) advanced a theory of competitive chunking for describing how a simple chunking mechanism might give rise to a more complex body of knowledge. In this theory, chunks are hierarchically organized traces in long-term memory. During learning, two sources of information are available to the competitive chunking processor: a chunk’s immediate subchunks, and a composite score of the chunk’s strength based on frequency and recency of use. The composite score determines the likelihood of chunk use and decays at a constant rate (simulating forgetting). Because chunks increase in strength with exposure to grammatical instances, learning is exhibited as an increase in chunk strength.

More specifically, when participants are exposed to letter sequences, the model matches single letters to the stimulus, resulting in chunks of length 1. On later iterations, letters are grouped into larger chunks until the entire sequence of letters forms a nesting of chunks. During test, grammaticality judgments vary as a function of the number of chunks produced when a new sequence is processed. If processing results in a small number of chunks (meaning that many of the chunks acquired during learning were used in parsing), then the letter sequence should result in a feeling of familiarity, leading to a judgment of grammaticality. In contrast, processing which results in a large number of chunks should lead to a judgment of nongrammaticality.

The competitive chunking model obtained high correlations between its
TABLE 1
Predictions of Computational Models of Artificial Grammar Learning in Terms of Complexity and Characteristics of Learning

<table>
<thead>
<tr>
<th>Learning complexity</th>
<th>Learning characteristics</th>
<th>Primary basis for judgments</th>
</tr>
</thead>
<tbody>
<tr>
<td>First-order dependencies</td>
<td>Second-order dependencies</td>
<td>Transfer</td>
</tr>
<tr>
<td>Servan-Schreiber &amp; Anderson (1990)</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Redington &amp; Chater (1996)</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Druhan &amp; Mathews (1989); Roussel et al. (1990)</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Cleeremans &amp; McClelland (1991); Cleeremans (1993)</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Dienes, Altmann, &amp; Gao (1995)</td>
<td>Yes</td>
<td>Yes</td>
</tr>
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predictions and actual subject performance during simulations performed by Servan-Schreiber and Anderson (1990). This model also finds empirical support in the work of Knowlton and Squire (1994, 1996) who demonstrated that grammaticality judgments were associated with chunk strength. However, the explanatory power of this model hinges on the relationship between familiarity and grammaticality judgments. In an empirical investigation of this relationship, Buchner (1994) found the role of familiarity in grammaticality judgments to be somewhat tenuous. In conducting this research, Buchner reasoned that familiar items ought to be identified more quickly under impoverished conditions than unfamiliar items, and if so, identification times should be related to grammaticality judgments. Using a perceptual identification procedure to measure the relative familiarity of grammatical and nongrammatical sequences, Buchner found that grammatical strings were identified more quickly than nongrammatical strings, but importantly, identification times were not correlated with grammaticality judgments. This finding does not entirely eliminate familiarity as a factor in grammaticality judgments, but does suggest that familiarity is not the only mediating factor (Buchner, 1994). Given the wealth of knowledge participants obtain in artificial grammar learning (Dulany et al., 1984; Mathews et al., 1989; Perruchet & Pacteau, 1990), Buchner suggested that application of knowledge retrieved via deliberate memory search might indeed be an important contributor to grammaticality judgments.

Another constraint on the competitive chunking model is that it contains no mechanism for generalizing to changed surface structure, and thus neither predicts, nor explains, transfer.

Recurrent Networks

Connectionist approaches to modeling implicit learning also emphasize the role of implicit processing differences over application of knowledge obtained via deliberate memory search. In one such approach, Cleeremans used a simple recurrent network (SRN) to model serial reaction time learning of a finite state system (Cleeremans, 1993; Cleeremans & McClelland, 1991). The SRN (Elman, 1990) consists of a layer of input units (representing elements at time \( t \)), a layer of hidden units and a context layer, and a layer of output units (representing elements at time \( t + 1 \)). The context layer holds a copy of the activation of units in the hidden layer at the previous time slice. When processing an element in sequence, activation is passed from the input units to the hidden units and on to the output units. The pattern of activation in the hidden layer is copied to the context units, and the procedure repeats in order to predict the next element. During learning, weights are changed using back propagation. Cleeremans’s model does not include a mechanism for mapping, and thus operates only in the domain in which it is trained. However, this network is capable of learning both first-order and second-order depend-
rences and provides a good fit to human data at this level of complexity (Cleeremans and McClelland, 1991).

In an effort to model transfer, Dienes et al. (1995) supplemented a standard SRN with mechanisms capable of learning mappings between domains. In their model input is encoded in one of two domains. Input feeds into the first hidden layer, element by element, where the units are recoded and then feed into the SRN. When processing an element in sequence, activation is passed from the recoded units in the first hidden layer to the hidden units in the second layer and on to the output units. Like the input units, the output units consist of two domains. The pattern of activation in hidden layer 2 is copied to the context units, and the procedure repeats in order to predict the next element. During learning, weights are changed using back propagation. At test, the network classifies a sequence as grammatical with regard to the degree with which it can predict successive elements in sequence. During transfer, the recurrent weights and the weights between hidden layers are frozen. Only the mapping weights (weights between domain 2 input and the first hidden layer and weights between the second hidden layer and domain 2 output) are changed. Essentially, the model learns a mapping between the old and new letters during exposure to the new letters in the transfer phase.

In simulating letters-same performance, Dienes et al. (1995) found that the network could approximate human grammaticality performance, given the same number of acquisition trials. In simulating transfer, Dienes et al. (1995) found that the model, like people, performed at approximately 70% of letters-same performance. One prediction of this model is that learning is entirely frequency based. There is no mechanism for representing rules involving salient letter patterns. Instead, transfer should be accomplished via an implicit mapping (in the hidden units) between acquisition and test domains. Another feature of storing knowledge in the pattern of activation in the hidden units, is that knowledge is abstracted away from specific surface features. Therefore, on this view specific features are not central to grammaticality judgments. That is, according to Dienes et al., grammaticality judgments are the direct result of more successful processing of grammatical compared to nongrammatical sequences (as opposed to deliberate memory search and application of specific knowledge).

Abstraction from Surface Features at Test

Another proposal suggests that instead of being stored in an abstract form, perhaps the information necessary for grammaticality performance is abstractable from knowledge of surface features at test (Redington & Chater, 1996). On this view then, grammaticality judgments are the result of memory retrieval rather than implicit processing differences. As a demonstration proof, Redington and Chater constructed simple models which use surface features of the acquisition sequences in making grammaticality judgments. The models judge sequences containing no novel surface features as “good” and those
containing novel surface features as ‘‘bad.’’ For instance, a model which has acquired the set of all trigrams as surface features would judge a sequence good if all of the trigrams in the sequence matched the set of acquired trigrams and bad if the sequence contained a trigram that could not be matched. During transfer to a sequence in the new letter set, a model attempts to find a consistent and unique mapping between the specified features of the acquisition set and the transfer letter set that results in no novel features.

Redington and Chater used several classes of models to investigate whether surface features combined with abstraction at test, would be consistent with empirical findings. For instance, one class of model assumed acquisition knowledge of all instances of certain feature types (e.g., all bigrams, trigrams, or legal letter beginnings). Another class of model only acquired information of bigrams or trigrams at the beginning and/or end of a sequence (e.g., initial bigrams, final bigrams, initial and final bigrams, initial trigrams, etc.). Redington and Chater compared the responses obtained with their models to those found in empirical data (e.g., Altmann et al., 1995; Brooks & Vokey, 1991; Gomez & Schvaneveldt, 1994; St. John & Shanks, in press; Whittlesea & Dorken, 1993). Models using bigram knowledge predicted empirical performance well for new sequences in the same letter set, but consistent with the findings of Gomez and Schvaneveldt (1994), the bigram-based models performed at chance in cases of violations of second-order dependencies and transfer. Interestingly, models using trigram features were able to predict transfer performance. Although the models’ performance levels greatly exceeded human performance, the patterns among conditions reflected those seen in empirical data (e.g., better performance in letter-same conditions compared to transfer).

The models proposed by Redington and Chater are meant only as demonstration proofs of the fact that grammaticality judgments can be executed with specific knowledge and thus do not address how this knowledge is acquired. However, this approach is consistent with the view that deliberate access to memory for specific surface features can indeed play an integral role in grammaticality performance. The fact that the models tend to overpredict performance may suggest that the extent of access embodied in the models is greater than that exhibited by human participants. That is, the low levels of grammaticality performance observed in human data, compared to the performance predicted using the Redington and Chater models, may be indicative of imperfect or incomplete knowledge of frequent or salient letter patterns.

Implicit Use of Partially Valid Rules

THIYOS, proposed by Mathews and colleagues (Druhan & Mathews, 1989; Mathews, 1991; Roussel, Mathews, & Druhan, 1990) embodies features of both implicit processing and deliberate memory search models. THIYOS represents learning of fragments or chunks using a classifier system based on
Holland, Holyoak, Nisbett, and Thagard’s (1986) induction theory and a forgetting algorithm. On the premise that participants’ rules are derived from partial memories of exemplars, THIYOS takes the verbal protocols of individual participants for use as partially valid condition-action rules which are then represented in the system by letter and location. Given the acquisition sequence ‘‘WWSNPZ,’’ the rule ‘‘Sequences beginning in ‘WWS’ are grammatical’’ is physically coded in a condition-action rule so that a match on this rule occurs any time the system encounters an exemplar beginning with ‘‘WWS.’’ The pattern and positional information for such a rule would be represented in THIYOS as WWS### (where # denotes any letter) and would be used to rate an exemplar like ‘‘WWSNPZ’’ more highly than ‘‘WWZ.’’

Given the sequences ‘‘WWSNPZ’’ and ‘‘WSSWSPNZ,’’ more abstract rules could be encoded as rr#### and #rr#####, where ‘‘rr’’ stands for a repeat of the immediately preceding letter. These rules then compete with each other in controlling the response selection in the grammaticality task. The strength of a rule is dependent on past effectiveness, the number of letter-positions the rule can account for, and the number of other rules converging on the same choice. Rules used to select the best match from a list of alternatives are incremented in strength relative to rules not used. Additionally, all the rules in the system are periodically reduced in strength in order to simulate forgetting of rules seldom or rarely used. Thus, rules are available via memory search, but rule strength (which contributes to the availability of a rule, and is influenced by use) directly contributes implicitly to response selection.

Druhan and Mathews (1989) used THIYOS to simulate human performance in a multiple choice sequence discrimination task. In the discrimination task participants chose one sequence from a set of five sequences containing zero, one, two, three, or four violations. Participants either generated rules for a group of unknown yoked participants and received feedback, or used the rules generated by the original group and received no feedback. The model successfully simulated human performance under both feedback and yoked/non-feedback conditions.

The learning predicted by THIYOS should extend to first-order dependencies, second-order dependencies based on positional knowledge of letter fragments, and transfer. However, instead of learning a mapping, this model predicts that transfer will be based on rules involving position of salient letter patterns such as alternations and repetitions. An advantage of this model is that it represents partial memories of both salient and frequent letter patterns, and thus both forms of knowledge should contribute to grammaticality judgments. With regard to the relationship between verbalizable and nonverbalizable knowledge, explicit processes alter the set of rules controlling behavior in THIYOS and implicit processes modify the strength of competing rules. By this view, participants should be aware of salient and/or frequent letter chunks and should show knowledge of these chunks, but the relative strength of rules is adjusted implicitly.
In summary, the complexity and specific characteristics of learning predicted by these models vary greatly. For instance, the mechanisms proposed by Servan-Schreiber and Anderson (1990) and Cleeremans and McClelland (1991) do not extend to transfer and thus cannot be considered viable candidates in an account of transfer without some modification (although they can account for learning of first- and second-order dependencies). The mechanisms proposed by Cleeremans and McClelland (1991), Dienes et al. (1995), and Servan-Schreiber and Anderson (1990) predict that implicit processing differences for grammatical and nongrammatical sequences should form the basis of grammaticality judgments, whereas a logical implication of the Redington and Chater (1996) approach is that grammaticality judgments are the consequence of retrieval and subsequent application of knowledge. Additionally, Cleeremans and McClelland (1991), Dienes et al. (1995), and Servan-Schreiber and Anderson (1990) predict learning based on frequency of transition (rather than salience of pattern or position), whereas Redington and Chater (1996) and Druhan and Mathews (1989) accommodate learning of both kinds of information. Finally, Dienes et al. (1995) predict that knowledge involved in grammaticality judgments is abstracted away from surface form, Redington and Chater (1996) predict that judgments will be induced from specific surface form, and Druhan and Mathews (1989) predict that both specific knowledge and abstract rules will contribute to grammaticality judgments.

ASSESSING THE RELATIONSHIP BETWEEN DELIBERATE ACCESS TO MEMORY AND INDIRECT TEST PERFORMANCE

A distinction bearing long-standing use in implicit memory (in contrast to implicit learning) defines direct tests as those which require conscious, or deliberate, access to memory for previous experiences, whereas indirect tests are those which can be executed without conscious, deliberate access to memory (Schacter, 1987). Examples of direct tests which have been used are recognition and recall. Examples of indirect tests are word stem completion and fragment completion. On this view, the reaction time measure used in sequence learning may be a better indicator of implicit learning than the grammaticality judgments used in the artificial grammar learning paradigm. In theory, the serial reaction time task can be performed without deliberate access to memory for previous learning instances (Perruchet, 1994; Seger, 1994b), whereas grammaticality judgments, like recognition judgments, require deliberate reference to the previous experience (Buchner, 1994; Dienes et al., 1991; Dulany et al., 1984; Mathews et al., 1989).

In addition to targeting appropriate indirect tests, it is also important to target appropriate direct tests. Simply asking a participant “if they know the rules” (an introspection procedure which has been used extensively in artificial grammar learning) will likely result in an incomplete or unrepresentative reflection of the participant’s knowledge. Recognition measures, on the other
hand, have some advantages over introspection. When participants have to respond to specific questions, they are less susceptible to the vagaries of free recall, such as failing to remember relevant information or reporting only a subset of what they know. Additionally, participants who exhibit no knowledge of a task, as measured by free recall, will often exhibit knowledge when they are probed with specific questions (Brewer, 1974), especially when the questions allow for an expression of degree of certainty (Dienes et al., 1991; Sanderson, 1989). Although recognition appears to be more sensitive than recall, recognition tests also have their problems (Dienes et al., 1991; Mathews et al., 1990). First, recognition tests are limited to detecting the specific information they are designed to find. Second, even though the participant is committed to giving a response to every probe, there is no clear indication as to whether the choice was the result of implicit or explicit knowledge.

An alternative to free recall and recognition is to probe participants for knowledge in the very context of the implicit learning task. Such an approach has been used extensively in SRT learning in the form of the generate task. Rather than pressing a key in response to the location of the stimulus (as is done during learning), participants are instructed to press the key which best predicts the next stimulus location (Perruchet & Amorim, 1992; Cohen et al., 1990; Hartman, Knopman, & Nissen, 1989; Nissen & Bullemer, 1987; Willingham, Nissen, & Bullemer, 1989; Willingham, Greeley, & Bardone, 1993). Research using this procedure shows that generation performance is highly associated with verbalizable knowledge of the sequence (Hartman et al., 1989; Willingham et al., 1989), suggesting that prediction should indeed be taken as a valid direct test.¹ Dienes et al. (1991) used a similar methodology in an artificial grammar learning paradigm. In their study, participants completed stems of various lengths with the next item in sequence in a test designed to measure sequential letter dependencies (SLD). The SLD measure was associated both with grammaticality performance and a verbal recall measure.

A technique which has been used in SRT learning, but not in artificial grammar learning, is that of grouping participants according to degree of deliberate access to knowledge (Curran & Keele, 1993; Hartman et al., 1989; Stadler, 1993; Willingham et al., 1989, 1993). The theoretical rationale for grouping participants in this way is to show that participants with virtually no awareness of the sequence still show implicit learning gains. For example, Willingham et al. (1989) used verbal reports in order to group participants according to low, medium, and high explicit knowledge. When participants were broken down in this way, the low group showed substantial gains in reaction-time performance regardless of the fact that they exhibited no deliber-

¹ Deciding on the most appropriate procedure for the generation task has been controversial (see Jimenez, Mendez, & Cleeremans [1996] and Perruchet & Amorim [1992]).
ate access to knowledge of the sequence. Willingham et al. also demonstrated that verbal reports were highly related to generation performance and to anticipatory responses. Such a demonstration is important for aligning the generation procedure with explicit, verbalizable knowledge.

An additional advantage of grouping participants according to degree of awareness is that it takes individual differences into account directly instead of assuming that such differences do not exist. When less aware and more aware participants are grouped together, it is not clear whether implicit learning is distributed across all participants or whether the effect is contributed primarily by a specific subset of the participants. The knowledge gains documented in implicit learning research tend to be modest, translating into very slight increases in performance (on the order of 10% in artificial grammar learning, and even lower in cases of transfer). Is it possible that some subset of participants have more deliberate access to knowledge than others and these are the same very same participants who are exhibit the highest indirect test scores? The only study to date on individual differences in implicit learning suggests not. In a study comparing artificial grammar learning to performance on a series solution-task, Reber, Walkenfeld, & Hernstadt (1991) found significantly less variability in performance on the indirect than the direct task. However, this study did not address cases of more complex learning such as learning second-order contingencies or transfer to new surface features.

On the assumption that direct measures require conscious, deliberate access to memory of acquisition items and indirect measures do not require deliberate access, recognition and prediction (a variant on generation and on the SLD task used by Dienes et al., 1991) were defined as direct measures, and reaction time and grammaticality judgments were defined as indirect measures. Participants were then tested for indirect knowledge under conditions of varying complexity. Given that grammaticality judgments may require deliberate access to memory, whereas sequential reaction time should not require such access, implicit learning should only be evidenced if participants show a significant degree of learning on the indirect but not on the direct measures.

Experiment 1 assessed the relationship of implicit and explicit learning using an artificial grammar learning paradigm. Experiment 2 applied the design and materials from Experiment 1 to a sequence-based grammar learning paradigm in which stimulus presentation and response were sequential rather than holistic in nature. The rationale for such an approach is that if both tasks are tapping into implicit processing, then participants should show similar learning patterns regardless of whether (1) information is presented holistically (in a manner preserving the salience of letter patterns) or sequentially (in a manner disrupting the salience of letter patterns), or (2) whether reaction time (used in Experiment 2) is a better operational measure of implicit learning than are the grammaticality judgments used in artificial grammar learning. Finally, because the Experiments 1 and 2 investigated the extent of
deliberate access to knowledge in the acquisition letter set, the objective of Experiment 3 was to investigate the extent of deliberate access to knowledge in the transfer letter set. The tests and stimuli used in these experiments were designed to tap into the kind of knowledge participants are known to obtain in implicit learning paradigms and with the same degree of sensitivity. The direct tests probed memory for bigrams and trigrams, whereas the indirect tests probed learning of first-order dependencies, second-order dependencies, and transfer. Given the assumption that indirect tests tap a greater component of implicit knowledge and a lesser component of explicit knowledge than do the direct tests, there were several outcomes of specific interest. First, participants could exceed control performance on the indirect tests (regardless of level of complexity) and fail to exceed control performance on the direct measures. Such an outcome would be consistent with interpretations of implicit learning which suggest that implicit and explicit learning are distinct, separable processes (e.g., Knowlton & Squire, 1994, 1996; Reber, 1989). Second, statistically significant performance on both direct and indirect tests in Experiment 1, but only on indirect tests in Experiment 2 would suggest that deliberate access to explicit knowledge is implicated in grammaticality performance, but not in reaction time. Third, the outcome in the first scenario could hold under simple conditions of learning complexity, but not under conditions of greater complexity. This outcome would be consistent with the view that deliberate access to memory may well be implicated in situations where abstraction is necessary for performing a task, such as transfer, but not in situations where abstraction is not needed (Perruchet, 1994).

**EXPERIMENT 1: ARTIFICIAL GRAMMAR LEARNING**

**Method**

Participants and Design

The participants were 180 undergraduates at New Mexico State University, fulfilling requirements for an introductory psychology course. There were four experimental groups and three conditions. Experiments 1 and 3 were run at the same, thus guaranteeing randomization of participants to all conditions. However, Experiment 3 will be presented after Experiment 2 for purposes of explication.

Shanks and St. John (1994) argued that although there is ample evidence for learning of specific events or fragments of training stimuli in implicit learning paradigms, the evidence that such learning is abstract and unavailable to consciousness is inconclusive. This is because the research to date largely fails to meet criteria which are fundamental for establishing the existence of an unconscious, abstract learning system. According to the information criterion, the information probed in the awareness test must map onto the information responsible for changes in performance on the implicit task. Furthermore, according to the sensitivity criterion the direct test must be equally as sensitive as the implicit performance task. Verbal reports (used extensively in implicit learning research) fail to meet the sensitivity criterion because the method by which they are obtained is so different from the means by which implicit learning is documented in
control groups. Thirty participants were randomly assigned to each experimental group and 20 were assigned to each control group. The experiment was conducted in several phases. Experimental participants participated in an acquisition phase first. Half of these participants then proceeded directly to the indirect tests; the other half participated in the direct tests first. All groups then participated in direct tests after the indirect test. One control group skipped the acquisition phase altogether and participated in the indirect test (followed by the direct test). The other two control groups participated in the direct tests only (one group per letter set). Indirect test controls participated in direct and indirect tests so if they performed above chance on the indirect test, it would be possible to determine whether these controls were also above chance on the direct measures.

Materials

Acquisition materials. Seventeen letter sequences, ranging in length from five to ten characters, were generated from the grammar shown in Fig. 1. These were used as training exemplars during the acquisition phase of the experiment (see Table 2). The sequences were instantiated in two letter sets (M, F, K, T, X and W, S, N, P, Z). Although the sequences did not exhaust the legal set, they were chosen to represent all paths through the grammar. Each sequence was presented six times during acquisition delimited by period marks ("."). Period marks were used to equate information concerning the beginning and ending positions in the holistic presentation of sequences used in Experiment 1 with the continuous letter-by-letter presentation used in Experiment 2.

Indirect test materials. Table 3 shows the 45 test sequences. Of these, 15 were new grammatical sequences, 15 were nongrammatical sequences with nonpermissible letter-pairs (NPP), and 15 were nongrammatical sequences with nonpermissible letter-triples (NPT) (taken from Perruchet & Pacteau, 1990; see also Gomez & Schvaneveldt, 1994). NPP violations were created by inserting an illegal pair into a grammatical test sequence. For example, SZ is illegal in the grammar so the grammatical sequence WWZ can be turned into an NPP sequence by inserting SZ in such a way as to obtain WSZ. This is in contrast to NPT violations which were created by inserting a legal pair in the wrong location in a sequence. For example, WWZ may be turned into an

4 In implicit learning studies, the direct test usually comes after the indirect test. However, in the interest of determining the degree to which knowledge affects performance, it may be more sensible to probe participants for deliberate access to memory directly after acquisition, especially in the case of transfer. Participants are likely to be somewhat perplexed after transfer, therefore the results of direct tests may not be as representative of what participants learned before being transferred to the new letter set. There are potential problems, however, with assessing knowledge in this order. First, probing for deliberate access to memory might switch participants from an incidental to an intentional learning mode. Several studies suggest that intentional strategies to learn interfere substantially with acquisition of the grammar (Brooks, 1978; Howard & Ballas, 1980; Reber, 1976; Reber et al., 1980; Turner & Fishler, 1993). However, probing should not interfere with acquisition, but only with performance on the indirect test. The second problem is more serious and must be ruled out. It is possible that participants could learn something from the direct tests that would enhance their performance on the indirect test. Thus, in Experiments 1 and 2 one group of participants were probed for deliberate access to memory before taking the indirect test and the other group were not probed until afterward. The two groups were then be compared in order to determine whether position of the direct test has substantial effects on performance.
TABLE 2
Acquisition Sequences Used for Same- and Different-Letter Participants
in Experiments 1, 2, and 3

<table>
<thead>
<tr>
<th>Same letters group: Letter-set 1</th>
<th>Different-letters (transfer) group: Letter-set 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>.WSWZ.</td>
<td>.MFMX.</td>
</tr>
<tr>
<td>.WSSWZ.</td>
<td>.MFFMX.</td>
</tr>
<tr>
<td>.WSWSNPZ.</td>
<td>.MFMMFKTX.</td>
</tr>
<tr>
<td>.WSWSPNZ.</td>
<td>.MFMMFTKX.</td>
</tr>
<tr>
<td>.WWSNPSNZ.</td>
<td>.MMFKTFKX.</td>
</tr>
<tr>
<td>.WWSPNZ.</td>
<td>.MMFTKX.</td>
</tr>
<tr>
<td>.WWNSNZ.</td>
<td>.MMFKKX.</td>
</tr>
<tr>
<td>.WSSWSNZ.</td>
<td>.MFMMFKKKX.</td>
</tr>
<tr>
<td>.WWSNSNZ.</td>
<td>.MFMMFKX.</td>
</tr>
<tr>
<td>.NPPNZ.</td>
<td>.KTTKX.</td>
</tr>
<tr>
<td>.NNZ.</td>
<td>.KKX.</td>
</tr>
<tr>
<td>.NPPNPZ.</td>
<td>.KTTKTX.</td>
</tr>
<tr>
<td>.NNPSPNPZ.</td>
<td>.KKTFTKTX.</td>
</tr>
<tr>
<td>.NNPSPNPZ.</td>
<td>.KKTFTKTX.</td>
</tr>
<tr>
<td>.NNPSPNPZ.</td>
<td>.KKTFTKTX.</td>
</tr>
<tr>
<td>.NPPZ.</td>
<td>.KTTX.</td>
</tr>
<tr>
<td>.NNFSNZ.</td>
<td>.KFTKX.</td>
</tr>
</tbody>
</table>

NPT sequence by inserting the legal pair SN in an illegal position to obtain WSNZ (in other words, a sequence with an illegal triple). In this case all first-order transitions are legal but the sequence as a whole is not. Detection of NPP violations requires knowledge of first-order dependencies, but detection of NPT violations requires knowledge of second-order dependencies and thus requires knowledge at a higher level of complexity.

Sequences were created in order to preserve as closely as possible the proportions of sequences of similar lengths in the study items. In previous studies participants showed substantial learning for anchor positions in letter sequences (Reber & Allen, 1978; Reber & Lewis, 1977), therefore the two outermost characters in a sequence (i.e., the period and the letter directly following or preceding the period) never entered into grammatical violations. Fifteen letter-sequences were generated for each of the three types of test sequences. Grammatical test sequences were presented twice and nongrammatical test sequences were presented once.

Direct test materials. The materials used to test participants differed only in terms of which letter set was used. For example, transfer participants were probed for explicit knowledge using the MFKTX letter-set (because they were exposed to this during acquisition) and participants in the letters-same condition were probed using the WSNPZ letter-set.

All pairwise combinations of the letters in the grammar were produced for the recognition test, resulting in 25 bigrams. Fourteen of the bigrams were legal; the remaining 11 were illegal. All three-way combinations of the letters and periods were also produced, resulting in 216 trigrams. Thirty-two of the trigrams were grammatical. Thirty-two additional nongrammatical trigrams were selected in order to make a set of stimuli containing 64 trigrams. Nongrammatical trigrams were chosen to match the violations found in the indirect test materials as closely as possible.

The items used in the prediction test consisted of the 14 legal bigrams and 32 legal trigrams.

Procedure

Participants were seated in front of PC compatible computers with standard keyboards. The experiment was entirely automated, but participants were encouraged to ask for help at any time.
### Indirect Test Sequences Used in Experiments 1, 2, and 3

<table>
<thead>
<tr>
<th>Grammatical sequences</th>
<th>NPP violations</th>
<th>NPT violations</th>
</tr>
</thead>
<tbody>
<tr>
<td>.WWZ.</td>
<td>.WNPNPZ.</td>
<td>.WSPNPZ.</td>
</tr>
<tr>
<td>.WWSNPZ.</td>
<td>.WPSNPNZ.</td>
<td>.WSSSNPZ.</td>
</tr>
<tr>
<td>.WWSWSNPZ.</td>
<td>.WSZ.</td>
<td>.WSSNPNZ.</td>
</tr>
<tr>
<td>.WWSPPNZ.</td>
<td>.WSWSPNZ.</td>
<td>.WSSWPNZ.</td>
</tr>
<tr>
<td>.WSWSNPZ.</td>
<td></td>
<td>.WSWPNZ.</td>
</tr>
<tr>
<td>.WSWPPNZ.</td>
<td>.WSWSNPNZ.</td>
<td>.WSWZ.</td>
</tr>
<tr>
<td>.WSWSWWNZ.</td>
<td></td>
<td>.NPSPNZ.</td>
</tr>
<tr>
<td>.NPNZ.</td>
<td>.NPNSNZ.</td>
<td>.WWNSZ.</td>
</tr>
<tr>
<td>.NNPSNPZ.</td>
<td></td>
<td>.NPNSNZ.</td>
</tr>
<tr>
<td>.NPNSNPNZ.</td>
<td></td>
<td>.WWWSNZ.</td>
</tr>
<tr>
<td>.NNPNSNZ.</td>
<td>.NPNSNZ.</td>
<td>.NPNSNPZ.</td>
</tr>
<tr>
<td>.NNPNSNPNZ.</td>
<td>.NPNSNPNZ.</td>
<td></td>
</tr>
<tr>
<td>.WWSSNSNZ.</td>
<td></td>
<td>.WWNSWNPZ.</td>
</tr>
<tr>
<td>.WWWSPNZ.</td>
<td></td>
<td>.WWNPNZ.</td>
</tr>
</tbody>
</table>

*Note.* Violations are marked in italics.

**Acquisition phase (typing task).** Participants were in one of four groups in the acquisition phase. They were trained on letter sequences in the same or in a different letter set than they would encounter on the indirect test. Participants were then further divided according to position of the direct tests (before or after the indirect test). Letter sequences were displayed on the computer screen for an amount of time proportional to the number of letters in the sequence. For example, a sequence such as .WSWZ. was displayed for 1200 ms (200 ms for each character in the sequence). Participants were instructed to study the sequence while it was displayed on the screen, and then to type it at the keyboard once it disappeared from view. If the participant typed the sequence correctly, the next sequence was presented, but in the case of an error, the sequence reappeared and the participant was prompted to type the sequence again. This procedure continued until the participant typed the sequence correctly. The 17 acquisition sequences were presented in a different random order in each of six blocks of trials. Participants received feedback on their error rate at the end of each block.

**Indirect test.** All participants were tested on sequences instantiated in the letters W, S, N, P, and Z regardless of whether they were trained on these or on the letters M, F, K, T, and X. Sequences were presented one at a time on the computer screen. The length of presentation was determined in the same manner as for acquisition items. Instructions were identical for both the letters-same and the transfer conditions; participants were informed that the sequences used in the typing task were determined by a complex set of rules allowing certain letters to follow other letters (controls were referred to the sequences they were about to see rather than the sequences from the typing task). Participants were then asked to discriminate new sequences which were valid instances of the rules from those which violated the rules. Participants made their choice by pressing the ‘‘y’’ key on the keyboard if they thought the sequence was valid and the ‘‘n’’ key if the sequence was invalid. The order of test sequences was determined randomly for each participant.

**Direct test assessment.** The purpose of this phase was to assess deliberate access to knowledge (first with a recognition test and then with a prediction test).

Participants completed 89 trials during the recognition test; 25 bigrams then 64 trigrams were
presented one at a time on the screen. Participants were asked whether they remembered that particular ordering of letters from the sequences presented during the typing task. Participants then rated their certainty on a 4-item scale from 1 to 4. Ratings of 4 indicated that the participant was certain of having seen the bigram or trigram embedded in a sequence during the typing task, whereas ratings of 1 indicated that the participant had not seen the letters in that order previously. Ratings of 2 and 3 indicated lesser degrees of certainty. The order of bigrams and trigrams was determined randomly for each participant.

Participants completed 46 trials during the prediction task. The first 14 trials used legal bigrams and the remaining 32 used legal trigrams. Participants were presented with a legal bigram or trigram, and were then asked to type the letter most likely to appear next in sequence. Participants were instructed to choose a legal continuation based on their memory for sequences presented during the typing task. Participants’ letter choices were limited to the letters in the same set for which they were currently being tested. The order of bigrams and trigrams was determined randomly for each participant. The prediction test was similar to the SLD task used by Dienes et al. (1991) with two exceptions: (1) participants in the present study completed items of length 2 and 3 only, and (2) bigrams and trigrams were taken from all positions in the grammar. In contrast, participants in the Dienes et al. study completed stems of length 0 through 5 (thus predicting locations 1 through 6), and all stems were initiated at the beginning of the grammar.

Scoring

Indirect test scores. Discrimination scores ($P_r$), based on two-high threshold theory, were computed by subtracting the proportion of false alarms (nongrammatical items mislabeled as grammatical items) from the proportion of hits (or correctly identified grammatical items). $P_r$ ranges from 0 (indicating no sensitivity) to 1 (indicating perfect discrimination).

Direct test scores. Recognition: $P_r$ scores were computed separately for bigram and trigram knowledge, thus placing recognition and grammaticality performance on comparable scales. Ratings of 3 and 4 were categorically scored as “yes” responses, whereas, ratings of 1 and 2 were scored as “no” responses.

Prediction test measures. Proportion correct was calculated separately for responses generated after bigrams and for those generated after trigrams, resulting in two prediction test measures. Responses to triples ending in “Z” or “X” were eliminated from the analyses because violations never occurred between the ending letter and the period.

Results and Discussion

Indirect Test Performance

The means and standard deviations for performance on the indirect test, for control and experimental groups are shown in Table 4. First, indirect-test controls were assessed for learning during the indirect test. $P_r$ was at chance levels both for NPP and NPT violations, ($t$s $< .08$, $p$s $> .95$), demonstrating that controls were not learning during the indirect test.

---

$^5$ Note that $P_r$ is identical to violation sensitivity, the measure used in Gomez & Schvaneveldt (1994), obtained by subtracting the proportion of misses from the proportion of correct rejections. An advantage in using $P_r$ is that this index can also be computed for recognition performance, thus placing recognition scores and grammaticality judgments on the same scale. I thank Axel Buchner for suggesting the use of this measure. Discrimination values were adjusted, as suggested by Snodgrass and Corwin (1988), in order to avoid undefined measures.
TABLE 4
Artificial Grammar Learning. Mean Discrimination (P_r) Scores for Nonpermissible Pair (NPP) and Nonpermissible Triple (NPT) Violations

<table>
<thead>
<tr>
<th>Violation type</th>
<th>NPP M (SD)</th>
<th>NPT M (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Controls</td>
<td>0.00 (0.12)</td>
<td>0.00 (0.14)</td>
</tr>
<tr>
<td>Letters-same^a</td>
<td>0.27 (0.14)</td>
<td>0.14 (0.18)</td>
</tr>
<tr>
<td>Direct test before indirect test</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Direct test after indirect test</td>
<td>0.34 (0.19)</td>
<td>0.13 (0.15)</td>
</tr>
<tr>
<td>Letters-different^b</td>
<td>0.07 (0.14)</td>
<td>0.05 (0.15)</td>
</tr>
<tr>
<td>Direct test before indirect test</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Direct test after indirect test</td>
<td>0.09 (0.14)</td>
<td>0.06 (0.15)</td>
</tr>
</tbody>
</table>

^a Comparisons for controls are to zero.
^b Comparisons for experimental groups are to the control group.

Next, a letter-set (letters-same vs letters-different) × position of direct test (before or after the indirect test) × violation-type (NPP vs NPT) ANOVA was conducted with the primary aim of determining whether the position of the direct test affected implicit learning performance. Transfer and position of the direct test were between-subjects variables; violation type was a within-subject variable. There were main effects of violation-type, \( F(1,116) = 51.19, MS_e = 0.01, \) (ps \( \leq .001 \) unless otherwise noted), and transfer, \( F(1,116) = 36.81, MS_e = 0.04, \) as well as an interaction involving these variables, \( F(1,116) = 24.82, MS_e = 0.01, \) but there were no main effects or interactions involving the position of the direct test (Fs < 2.65). The letter-set by violation-type interaction reflects the fact that the magnitude of the difference between NPP and NPT violations is greater for letters-same than for letters-different participants.

Given that indirect test performance did not vary significantly with position of the direct test, indirect test scores for the experimental groups were collapsed across position of the direct test. Letters-same participants showed a significant degree of learning, compared to controls, as measured by sensitivity both to NPP violations, \( t(78) = 7.24, M = 0.30, SD = 0.17, \) and to NPT violations, \( t(78) = 3.37, M = 0.14, SD = 0.16. \) Transfer participants showed a significant degree of sensitivity to NPP violations, \( t(78) = 2.27, p = .026, M = 0.08, SD = 0.14, \) but not to NPT violations, \( t(78) = 1.38, p = .173, M = .05, SD = .15. \)

Direct Test Performance
Next, performance was assessed on the direct tests. The analyses consisted of comparisons between the experimental and control groups. Table 5 shows
TABLE 5
Mean Recognition Performance Associated with the Presentation of a Bigram or Trigram after Artificial Grammar Learning

<table>
<thead>
<tr>
<th>Condition</th>
<th>Recognition - P_r</th>
<th>Bigrams</th>
<th>Trigrams</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>M (SD)</td>
<td>M (SD)</td>
</tr>
<tr>
<td>Letters-same^a</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls (letter-set 1)</td>
<td></td>
<td>.10 (.14)</td>
<td>.06 (.09)</td>
</tr>
<tr>
<td>Direct test before indirect test</td>
<td></td>
<td>.38 (.15)</td>
<td>.33 (.16)</td>
</tr>
<tr>
<td>Direct test after indirect test</td>
<td></td>
<td>.42 (.18)</td>
<td>.30 (.17)</td>
</tr>
<tr>
<td>Letters-different^b</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls (letter-set 2)</td>
<td></td>
<td>.12 (.14)</td>
<td>.06 (.10)</td>
</tr>
<tr>
<td>Direct test before indirect test</td>
<td></td>
<td>.31 (.23)</td>
<td>.27 (.19)</td>
</tr>
<tr>
<td>Direct test after indirect test</td>
<td></td>
<td>.36 (.22)</td>
<td>.34 (.22)</td>
</tr>
</tbody>
</table>

*a* Letters-same performance was compared to direct test control performance for Letter-set 1.

*b* Letters-different performance was compared to direct test control performance for Letter-set 2.

Mean recognition performance for bigrams and trigrams. The top half of Table 5 shows recognition scores for the letters-same control and experimental groups. The second half of Table 5 shows the recognition scores for the letters-different control and experimental groups. Because the direct tests were used to probe knowledge resulting from the acquisition phase, letters-same groups were assessed on Letter-set 1 and letters-different groups were assessed on Letter-set 2. First, $t$ tests were used to determine whether direct test performance was affected by the indirect test (analysis of variance was not used because letter-same and letter-different acquisition knowledge was assessed on different letter sets). There were no differences in bigram or trigram recognition for participants who took the direct tests before the indirect test relative to those who did not take the direct tests until afterward, ($t$s < 1.26, $p$s > .214), thus performance was collapsed across position of the direct test. The experimental groups scored above controls on their ability to discriminate legal from illegal bigrams and trigrams regardless of whether they were transferred to the same or different letter set on the grammaticality task (for letters-same participants, $M = 0.40$, $SD = 0.17$ for bigram recognition and $M = 0.32$, $SD = 0.16$ for trigram recognition; for letters-different participants, $M = 0.34$, $SD = 0.22$ for bigram recognition and $M = 0.31$, $SD = 0.21$ for trigram recognition, $t$s > 4.08).

Table 6 shows proportion correct performance on the prediction test and is organized in the same manner as Table 5. As with recognition performance, $t$ tests were used to determine whether direct test performance was affected by
TABLE 6
Mean Accuracy for Predicting a Letter following a Legal Bigram or Trigram, after Artificial Grammar Learning

<table>
<thead>
<tr>
<th>Condition</th>
<th>Bigrams M (SD)</th>
<th>Trigrams M (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Letters same&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls (letter-set 1)</td>
<td>.50 (.17)</td>
<td>.41 (.09)</td>
</tr>
<tr>
<td>Direct test before indirect test</td>
<td>.69 (.19)</td>
<td>.63 (.11)</td>
</tr>
<tr>
<td>Direct test after indirect test</td>
<td>.72 (.12)</td>
<td>.65 (.13)</td>
</tr>
<tr>
<td>Letters-different&lt;sup&gt;b&lt;/sup&gt;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls (letter-set 2)</td>
<td>.51 (.16)</td>
<td>.40 (.10)</td>
</tr>
<tr>
<td>Direct test before indirect test</td>
<td>.65 (.18)</td>
<td>.60 (.13)</td>
</tr>
<tr>
<td>Direct test after indirect test</td>
<td>.70 (.19)</td>
<td>.63 (.14)</td>
</tr>
</tbody>
</table>

<sup>a</sup> Letters same performance was compared to direct test control performance for Letter-set 1.
<sup>b</sup> Letters-different performance was compared to direct test control performance for Letter-set 2.

The indirect test. There were no differences in prediction after bigrams or trigrams resulting from position of the direct tests ($t$s < 1.12, $p$s > .267), thus performance was again collapsed across this variable. The experimental groups scored above controls on their ability to predict the next item in sequence following legal bigrams and trigrams regardless of whether or not they were transferred to a different letter set on the grammaticality task (for letters-same participants, $M = 0.71, SD = 0.16$ for prediction following bigrams and $M = 0.64, SD = 0.12$ for prediction following trigrams; for letters-different participants, $M = 0.68, SD = 0.19$ for prediction following bigrams and $M = 0.61, SD = 0.13$ for prediction following trigrams, $t$s > 3.46).

Levels Analyses

Next, participants were grouped separately according to recognition and prediction performance. Participants were classified as high, medium, or low on direct test knowledge as follows. First, participants were ranked according to bigram and trigram knowledge. Then the ranks were averaged in order to identify which participants were in the bottom, middle, or upper third of scores. In some cases, participants did not divide evenly into groups of 20 because of ties, therefore, the distributions of participants’ ranks were examined individually in order to determine reasonable dividing points. Low knowledge groups were chosen with the additional constraint that they should not differ significantly from the controls on the explicit knowledge measures.

The analyses consisted of a number of planned comparisons between the
TABLE 7

Experiment 1: Artificial Grammar Learning—Mean Discrimination as a Function of Recognition Knowledge (Low, Medium, High)*

<table>
<thead>
<tr>
<th>Condition (N)</th>
<th>M (SD)</th>
<th>M (SD)</th>
<th>M (SD)</th>
<th>M (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bigrams</td>
<td>Trigrams</td>
<td>NPP</td>
<td>NPT</td>
</tr>
<tr>
<td>Low (10)</td>
<td>.20 (.12)</td>
<td>.11 (.11)</td>
<td>.22 (19)*</td>
<td>.06 (.15)</td>
</tr>
<tr>
<td>Medium (25)</td>
<td>.35 (.13)*</td>
<td>.27 (.11)*</td>
<td>.28 (.17)*</td>
<td>.13 (.18)*</td>
</tr>
<tr>
<td>High (25)</td>
<td>.53 (.09)*</td>
<td>.45 (.11)*</td>
<td>.36 (.15)*</td>
<td>.17 (.14)*</td>
</tr>
<tr>
<td>Low (18)</td>
<td>.12 (.15)</td>
<td>.11 (.12)</td>
<td>.08 (16)</td>
<td>.07 (.16)</td>
</tr>
<tr>
<td>Medium (17)</td>
<td>.27 (.13)*</td>
<td>.26 (.09)*</td>
<td>.06 (.12)</td>
<td>.03 (.14)</td>
</tr>
<tr>
<td>High (25)</td>
<td>.53 (.14)*</td>
<td>.49 (.14)*</td>
<td>.10 (.14)*</td>
<td>.05 (.16)</td>
</tr>
</tbody>
</table>

* The p values associated with each mean are for t tests comparing the participants in that group to the appropriate controls. Thus indirect test performance was compared to the indirect test controls shown in Table 4. Direct test performance for the letters-same group was compared to the Letter-set 1 control performance shown in the top half of Table 5. Direct test performance for the letters-different group was compared to the Letter-set 2 control performance shown in the bottom half of Table 5.

* p ≤ .05.

experimental and control groups. A more stringent criterion than the one used here (p = .05) could have been chosen in order to control for inflated Type I errors. However the objective in the present studies is to learn more about the relationship between direct and indirect test performance, and overly stringent significance criteria could act in the opposite direction by inflating Type II error rates, thereby eliminating important information. It is also worth noting that an alternate method of analysis would be to use correlations in place of a levels analysis. However, correlations would not show what happens to indirect test performance for participants who perform no better than controls on the direct tests.

Recognition. Table 7 shows a breakdown of mean sensitivity to NPP and NPT violations as a function of recognition performance. Participants were divided into low, medium, and high knowledge groups as described above.

In the letters-same condition, low knowledge participants showed no difference relative to controls on the direct tests, ts ≤ 2.00, ps > .05, whereas medium and high knowledge participants were significantly higher than controls, ts ≥ 6.24. Although low knowledge participants failed to exceed control performance on recognition, this same group still showed a significant degree of sensitivity to NPP violations, t(28) = 3.92, but not to NPT violations, t(28)
TABLE 8
Experiment 1: Artificial Grammar Learning—Mean Discrimination as a Function
of Prediction Performance (Low, Medium, High)

<table>
<thead>
<tr>
<th>Condition (N)</th>
<th>Direct test: Prediction</th>
<th>Indirect test: Discrimination (P_r)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bigrams</td>
<td>Trigrams</td>
</tr>
<tr>
<td>Letters-same</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low (13)</td>
<td>.52 (.09)</td>
<td>.47 (.10)</td>
</tr>
<tr>
<td>Medium (28)</td>
<td>.70 (.14)*</td>
<td>.65 (.07)*</td>
</tr>
<tr>
<td>High (19)</td>
<td>.84 (.10)*</td>
<td>.73 (.06)*</td>
</tr>
<tr>
<td>Letters-different</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low (9)</td>
<td>.43 (.11)</td>
<td>.44 (.07)</td>
</tr>
<tr>
<td>Medium (36)</td>
<td>.65 (.14)*</td>
<td>.59 (.09)*</td>
</tr>
<tr>
<td>High (15)</td>
<td>.88 (.10)*</td>
<td>.76 (.06)*</td>
</tr>
</tbody>
</table>

* The p values associated with each mean are for t tests comparing the participants in that group to the appropriate controls. Thus indirect test performance was compared to the indirect test controls shown in Table 4. Direct test performance for the letters-same group was compared to the Letter-set 1 control performance shown in the top half of Table 6. Direct test performance for the letters-different group was compared to the Letter-set 2 control performance shown in the bottom half of Table 6.

* p ≤ .05.

= 1.09, p = .283. In contrast, the medium and high knowledge participants showed a significant degree of sensitivity to both NPP and NPT violations, ts ≥ 2.63, ps ≤ .012.

In the letters-different condition, low knowledge participants showed no difference relative to controls on the direct tests, ts ≤ 0.96, ps ≥ .343, whereas medium and high knowledge subjects were significantly higher on recognition than controls, ts ≥ 3.54. In contrast to the letters-same condition, the only evidence for transfer occurred for participants in the high knowledge group on sensitivity to NPP violations, t(43) = 2.43, p = .019, (all other ts ≤ 1.73).

Prediction. Table 8 shows a breakdown of mean sensitivity to NPP and NPT violations as a function of prediction performance.

In the letters-same condition, low knowledge participants showed no difference relative to controls on the direct tests, ts ≤ 1.69, ps ≥ .10, whereas medium and high knowledge participants were significantly above controls, ts ≥ 4.44. Although low knowledge participants failed to exceed control performance on prediction, this same group showed a significant degree of sensitivity to NPP violations, t(31) = 4.20, but not to NPT violations, t(31)
In contrast, the medium and high knowledge participants showed a significant degree of sensitivity to both NPP and NPT violations, $t_s \geq 3.07$, $p_s \leq .004$.

In the transfer condition, low knowledge participants showed no difference relative to controls on the direct tests, $t_s \leq 1.17$, $p_s \geq .251$, whereas medium and high knowledge subjects were significantly higher on prediction than were controls, $t_s \geq 3.35$. In contrast to the letters-same condition, the only evidence for transfer occurred for sensitivity to NPP violations in the high knowledge group, $t(33) = 2.08$, $p = .045$. The medium knowledge group showed marginal evidence for sensitivity to NPP violations, $t(54) = 1.96$, $p = .055$, but all other $t_s \leq 1.74$, $p_s \geq .091$.

The objectives of Experiment 1 were to (1) assess the degree to which performance in artificial grammar learning was accompanied by significant performance on direct tests, (2) determine whether deliberate access to knowledge was an important factor in cases of greater complexity, and (3) assess how position of the direct tests affected both direct and indirect test performance. The overall analysis suggested that the position of the direct tests had no substantial effect on performance in the indirect test, however examination of Table 4 shows that indirect test performance for participants taking the direct test before the indirect test was slightly lower compared to means for participants who took the direct tests afterward. This is not surprising given that participants were exposed to illegal bigrams and trigrams during the recognition test and might have incorporated this information into their knowledge of the grammar. Transfer tends to be attenuated relative to letter-same performance, and exposure to illegal information or the time delay produced by participation in the direct tests, may produce some interference with an already fragile knowledge base. Interestingly, even though direct test performance increased slightly, the increase was not significant, suggesting that reliable assessments of direct test knowledge can indeed be obtained after the indirect test.

Contrary to strong claims for a dissociation between grammaticality judgments and awareness, direct test performance exceeded that of controls using both recognition and prediction procedures. These results replicate previous findings showing significant degrees of awareness for letter patterns after artificial grammar learning (e.g., Dienes et al., 1991; Mathews et al., 1989). However, in order to determine whether deliberate access to knowledge was associated with grammaticality performance, participants were grouped according to direct test performance. Given the findings reported in previous research using such a methodology (Curran & Keele, 1993; Hartman et al., 1989; Stadler, 1993; Willingham et al., 1989, 1993), it was hypothesized that low knowledge participants (who did not differ from controls on the direct tests) would certainly show some evidence of implicit learning in the absence of explicit knowledge. Interestingly, this was the case for learning first-order dependencies (as measured with sensitivity to NPP-type violations). However,
low knowledge groups failed to show learning for second-order dependencies (measured with sensitivity to NPT violations) or the ability to generalize to stimuli with the same underlying rule structure but different surface characteristics. It should also be noted that the numbers of low knowledge participants were particularly small. However it was difficult to find participants who did not exceed control performance on the direct tests, suggesting that most participants have a great deal of deliberate access to knowledge of specific surface structure.

The pattern of results in Experiment 1 is significant for several reasons. First, it should be noted that the direct tests meet the rigors of both information and sensitivity criteria (Shanks & St. John, 1994). That is, the same information involving bigrams and trigrams is probed in the direct and indirect tests (satisfying the information criterion). Additionally, the recognition test appears to be as sensitive, if not more so, than the grammaticality test as evidenced by the fact that mean $P_r$ scores were higher for the direct than for the indirect test. One might argue that the prediction test is less sensitive than grammaticality judgments, but, given that the retrieval required of prediction is a more difficult and stringent test of knowledge than recognition, the results for prediction provide important converging evidence. Finally, the results found for low knowledge participants demonstrate that people can learn first-order dependencies even when there is little evidence for deliberate access to knowledge. However, deliberate access to knowledge of letter patterns seems to be more important for learning of greater complexity given the findings that low knowledge participants performed poorly when tested on knowledge of second-order dependencies and transfer whereas high knowledge participants performed well.

**EXPERIMENT 2: SEQUENCE-BASED GRAMMAR LEARNING**

Experiment 2 addressed the issue of whether grammaticality judgments are more like direct or indirect measures by using the same design and materials as Experiment 1, but in the context of a sequential grammar learning paradigm. In sequence-based grammar learning, participants respond to stimuli presented in a continuous letter-by-letter manner so that learning can be assessed via reaction time rather than grammaticality judgments. The advantage of using reaction time over grammaticality judgments is that participants are not explicitly instructed to access their memory for previous instances as is done with grammaticality instructions. In contrast to encouraging participants to use the knowledge they obtain during acquisition to make grammaticality judgments (as is done in artificial grammar learning), reaction time to type a letter should not require deliberate access to memory for specific sequences. Participants in Experiment 2 saw one letter at a time in the center of the screen and their task was to type the corresponding key on the keyboard. After typing the correct key, the next letter replaced the previous letter in the center of the screen, and so on, for the entire set of sequences. There were no time delays.
between presentation of sequences, with the only demarcation between one sequence and the next being a period.

The primary difference between SRT learning and sequence-based grammar learning is that the former involves responding to a fixed sequence of stimulus locations with spatially related response keys. In sequence-based grammar learning, however, there is no spatial relationship between stimulus and response location (participants place their hands on the keyboard in the manner of typists). This procedure was chosen over the typical sequence learning paradigm because it retains the informational aspects of artificial grammar learning, but varies stimulus presentation and response sequentially, thus resulting in a reaction time measure of learning which can be contrasted with grammaticality judgments. Sequential presentation should also interfere with the spatial cues contributing to the salience of frequent letter patterns when a entire sequence is presented (as in the standard artificial grammar learning paradigm).

Additionally, one discrepancy between the models proposed by Cleeremans and McClelland (1991) and Dienes et al. (1995) and the way human learners may function is that these models process letters in a passive, sequential fashion, whereas experimental participants may well rely on an active chunking strategy during acquisition. Such a strategy might be more likely to result in explicit knowledge of chunks. It is impossible to control active chunking when sequences are presented holistically, but active chunking could be controlled with sequential presentation, thus resulting in a closer match to the way information enters the models proposed by Cleeremans and McClelland (1991) and Dienes et al. (1995). Furthermore, these models predict that judgments of grammaticality should follow from differences in processing grammatical versus nongrammatical sequences, however, it is impossible to observe ease of processing in the context of the grammaticality task. Thus, an alternative is to retain the informational aspects of the grammaticality task but to use reaction time to sequential transitions to assess ease of processing. Given the results found in SRT learning where participants respond faster to legal versus illegal transitions (e.g., Cleeremans & McClelland, 1991), participants in Experiment 2 should respond similarly.

Given that the stimuli were identical in both experiments, questions of interest have to do with determining whether or not the same patterns of learning that occurred in Experiment 1 will also occur when (1) the salience of frequent patterns is altered by sequential (rather than holistic) presentation and (2) the measure of learning does not require deliberate access to memory for specific instances. Evidence for implicit learning will occur if performance on the indirect test exceeds control performance, but direct test performance does not exceed that of controls.

Method

Participants and Design

The participants were 140 undergraduates at New Mexico State University fulfilling partial requirements for an introductory psychology course (120 experimental participants and 20 control
participants). Participants were randomly assigned to one of four groups: letters-same or letters-different (transfer) group versus position of the direct tests. The data from the 40 direct-test control participants who participated in the recognition and prediction tasks in Experiment 1 were also used in this study.

Materials

The stimuli were identical to those used in Experiment 1.

Procedure

The procedure was identical during the acquisition and indirect test phase: participants typed in letter sequences, but instead of typing a whole sequence, participants typed a series of continuous sequences. Each character was displayed in the center of the screen and participants were instructed to type the character as quickly and accurately as possible. The character remained in view until the participant typed it correctly. The next character in sequence was presented 200 ms later (in the center of the screen). All acquisition sequences were presented once in each of six blocks of trials. The order of presentation was randomized for each block. Participants were given feedback on error rate and mean reaction time at the end of each block. The 20 control participants skipped the acquisition phase and participated in the indirect test followed by the direct tests.

Explicit knowledge assessment. The procedure and materials used for assessing explicit knowledge were identical to those used in Experiment 1, except that bigrams and trigrams were presented one letter at a time in order to mimic the sequential presentation of letters during the acquisition and indirect test phases. Participants were not asked to respond to the sequential presentation of stimuli; they were merely required to observe before making a recognition judgment or predicting the next item in sequence.

Scoring

The difference in reaction time to respond to correct grammatical versus non-grammatical transitions served as the measure of implicit learning. Reaction times were trimmed to within 2 \( \pm \frac{1}{2} \) standard deviations of the mean. Grammatical transitions were identified by matching the stems preceding non-grammatical transitions in the NPP and NPT sequences to grammatical sequences. Thus, the series of letters preceding key grammatical and non-grammatical transitions were identical. Because there was more than one grammatical transition for every nongrammatical transition, a mean was taken for all correct responses to grammatical transitions. This mean was used in computing reaction time differences between grammatical and non-grammatical transitions. Completions involving repetitions (e.g. "SS") were not included in this analysis as reaction times to repetitions tend to be fast for reasons that may be independent of learning. The recognition and prediction test measures were computed exactly as in Experiment 1.

Results and Discussion

Indirect Test Performance

The means and standard deviations for performance on the indirect test, for control and experimental groups are shown in Table 9. First, control performance was examined to determine if learning occurred during the indirect test. The mean reaction time difference was significantly greater than 0 for NPP transitions, \( t(19) = 6.79 \) (all \( ps \leq .001 \) unless otherwise noted), but not for NPT transitions, \( t(19) = -.08, p = .937 \). Deliberate access to knowledge was then assessed by comparing this group’s direct test performance
TABLE 9
Sequence-Based Grammar Learning—Difference in Mean Reaction Times (in milliseconds) to Respond to Nongrammatical Versus Grammatical Letter Transitions

<table>
<thead>
<tr>
<th>Violation type</th>
<th>Condition</th>
<th>NPP M (SD)</th>
<th>NPT M (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Controls</td>
<td>106 (70)</td>
<td>-1 (48)</td>
</tr>
<tr>
<td></td>
<td>Letters-same</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Direct test before indirect test</td>
<td>134 (96)</td>
<td>54 (78)</td>
</tr>
<tr>
<td></td>
<td>Direct test after indirect test</td>
<td>130 (90)</td>
<td>30 (51)</td>
</tr>
<tr>
<td></td>
<td>Letters-different</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Direct test before indirect test</td>
<td>85 (93)</td>
<td>10 (88)</td>
</tr>
<tr>
<td></td>
<td>Direct test after indirect test</td>
<td>112 (76)</td>
<td>23 (55)</td>
</tr>
</tbody>
</table>

*a* Comparisons for controls are to zero.

*b* Comparisons for experimental groups are to the control group.

(Obtained after participation in the indirect test) to that of direct test controls taken from Experiment 1. Mean performance for the Experiment 2 control group was $M = .10, SD = .19$ for bigram recognition, $M = .08, SD = .064$ for trigram recognition, $M = .55, SD = .22$ for prediction after bigram presentation, and $M = .39, SD = .14$ for prediction after trigram presentation. Mean performance for the direct test control group was $M = .10, SD = .14$ for bigram recognition, $M = .06, SD = .09$ for trigram recognition, $M = .50, SD = .17$, for prediction after bigram presentation, and $M = .41, SD = .09$, for prediction after trigram presentation. There were no differences between the control group and the direct test controls on any of the direct tests, $t_s \leq 1.01, ps \geq .323$. This pattern of results demonstrates that learning of first-order dependencies (as measured by sensitivity to NPP violations) was indeed occurring during the indirect test, but such learning appears to be implicit because the indirect test controls performed no differently on recognition and prediction tests than controls who had no previous exposure to the grammar.

As in Experiment 1, an overall ANOVA (with transfer and position of the direct test as between-subjects variables and violation-type as a within-subject variable) was conducted with the primary aim of determining whether the position of the direct test would affect sequential grammar learning performance (see Table 9). Instead of using discrimination, however, the dependent measure was the mean reaction time difference between grammatical and nongrammatical transitions. There were no main effects or interactions involving the position of the direct test. This was a replication of the results found in Experiment 1 for the position of the direct tests. There was a main effect of violation-type, $F(1,116) = 104.88, MS_e = 4,237.64$; the mean reaction
time difference to NPP violations was 115 ms and 29 ms to NPT violations. There was also a main effect of transfer, \( F(1,116) = 6.27, MS_e = 8.557.80; \) the mean reaction time difference decreased from 87 ms in the letters-same condition to 57 ms for participants who transferred to a different letter set.

Given that there were no differences in sequence-based grammar learning as a function of the position of the direct tests, performance was collapsed across this variable. Participants receiving the same letter set between acquisition and test showed no advantage compared to indirect test controls as measured by reaction time differences to NPP violations versus grammatical transitions, \( t(78) = 1.15, p = .254, M = 132.28, SD = 92.53. \) However, this group did outperform controls on sensitivity to NPT violations, \( t(48) = 2.67, p = .009, M = 42.13, SP = 66.32. \) The failure for the experimental group to outperform controls on sensitivity to NPP violations suggests that learning of first-order dependencies occurs early and increases little with practice, however, sensitivity to NPT violations appears to develop more slowly. In contrast to Experiment 1, sequence-based grammar learning resulted in no transfer to new surface characteristics. Mean reaction time differences failed to exceed control performance regardless of violation type, \( M = 98.3, SD = 84.88 \) for NPP violations, and \( M = 16.32, SD = 73.33 \) for NPT violations, \( ts \leq 1.978, ps \geq .331. \) The failure to find transfer suggests that sequence-based grammar learning is confined to learning the specific surface structure of stimuli.

**Direct Test Performance**

Table 10 shows recognition performance for bigrams and trigrams. The top half of Table 10 shows recognition scores for the letters-same control group and experimental groups. The bottom half of Table 10 shows the recognition scores for the letters-different control group and the experimental groups. Standard deviations are shown in parentheses. First, \( t \) tests were used to determine whether direct test performance was affected by the indirect test. There were no differences in bigram or trigram recognition for participants who took the direct tests before the indirect test relative to those who did not take the direct tests until afterward, \( ts \leq 1.81, ps \geq .075. \) Therefore, performance was collapsed across this variable. In contrast to Experiment 1 where each experimental group scored above the direct test controls, fewer groups scored above the controls in Experiment 2. Participants in the letters-same condition scored above controls on both recognition measures, \( M = .23, SD = .27 \) for bigram recognition and \( M = .17, SD = .17 \) for trigram recognition \( (ts \geq 2.06, ps \leq .043). \) None of the participants in the transfer condition showed statistically significant recognition performance, \( M = .15, SD = .18 \) for bigram recognition and \( M = .08, SD = .14 \) for trigram recognition \( (ts \leq .67, ps \geq .503). \)

Table 11 shows proportion correct performance on the prediction test and is organized in the same manner as Table 10. There were no differences in
TABLE 10
Sequence-Based Grammar Learning: Mean Bigram and Trigram Recognition Performance

<table>
<thead>
<tr>
<th>Condition</th>
<th>Bigrams</th>
<th>Trigrams</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M (SD)</td>
<td>M (SD)</td>
</tr>
<tr>
<td>Letters-samea</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls (letter-set 1)</td>
<td>.10 (.14)</td>
<td>.06 (.09)</td>
</tr>
<tr>
<td>Direct test before indirect test</td>
<td>.17 (.22)</td>
<td>.13 (.16)</td>
</tr>
<tr>
<td>Direct test after indirect test</td>
<td>.29 (.30)</td>
<td>.20 (.18)</td>
</tr>
<tr>
<td>Letters-differentb</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls (letter-set 2)</td>
<td>.12 (.14)</td>
<td>.06 (.10)</td>
</tr>
<tr>
<td>Direct test before indirect test</td>
<td>.16 (.19)</td>
<td>.10 (.15)</td>
</tr>
<tr>
<td>Direct test after indirect test</td>
<td>.14 (.16)</td>
<td>.06 (.10)</td>
</tr>
</tbody>
</table>

a Letters-same performance was compared to direct test control performance for Letter-set 1.
b Letters-different performance was compared to direct test control performance for Letter-set 2.

prediction as a function of the position of the direct tests, \((ts \leq 1.81, ps \geq .075)\), therefore performance was also collapsed across this variable. Letters-same participants scored above controls for correctly predicting the letter following a bigram, \(M = .66, SD = .20\), and for correctly predicting the letter following a trigram, \(M = .48, SD = .14\) \((ts \geq 2.06, ps \leq .043)\). None of the letters-different participants scored above controls on the prediction test, \(M = .44, SD = .17\) for prediction following bigrams and \(M = .38, SD = .10\) for prediction following trigrams, \((ts \leq 1.70, ps \geq .093)\).

The primary objective of Experiment 2 was to compare the pattern of results obtained for sequence-based grammar learning to those obtained in Experiment 1 for artificial grammar learning. The acquisition phases in the two experimental paradigms were identical except for the manner in which sequences were presented. In artificial grammar learning, the stimuli were presented holistically requiring participants to hold entire sequences in short-term memory while executing the typing task. In the sequence-based grammar learning paradigm, stimuli were presented in a continuous manner which only required participants to respond to one character at a time before going on the next character in sequence. This contrast between a holistic and continuous presentation of information was further preserved in the indirect tests with artificial grammar learning participants making grammaticality judgments based on whole sequences and sequence-based grammar learning participants merely responding to items in a continuous sequence. Responding to items in a sequence by typing the letter may be a better measure of implicit learning than grammaticality judgments because the latter encourages participants to
TABLE 11
Sequence-Based Grammar Learning: Mean Accuracy for Predicting a Letter following a Legal Bigram or Trigram

<table>
<thead>
<tr>
<th>Condition</th>
<th>Prediction: Proportion correct</th>
<th>Bigrams M (SD)</th>
<th>Trigrams M (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Letters-same</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls (letter-set 1)</td>
<td>.50 (.17)</td>
<td>.41 (.09)</td>
<td></td>
</tr>
<tr>
<td>Direct test before indirect test(a)</td>
<td>.65 (.21)</td>
<td>.45 (.15)</td>
<td></td>
</tr>
<tr>
<td>Direct test after indirect test</td>
<td>.67 (.18)</td>
<td>.52 (.13)</td>
<td></td>
</tr>
<tr>
<td>Letters-Different</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls (letter-set 2)</td>
<td>.51 (.16)</td>
<td>.40 (.10)</td>
<td></td>
</tr>
<tr>
<td>Direct test before indirect test(a)</td>
<td>.47 (.17)</td>
<td>.38 (.12)</td>
<td></td>
</tr>
<tr>
<td>Direct test after indirect test</td>
<td>.41 (.17)</td>
<td>.37 (.08)</td>
<td></td>
</tr>
</tbody>
</table>

\(a\) Letters-same performance was compared to direct test control performance for Letter-set 1. 
\(a\) Letters-different performance was compared to direct test control performance for Letter-set 2.

These results suggest that serial reaction times may provide information not obtainable from grammaticality judgments, as evidenced by the fact that sequence-based grammar learning controls showed rapid learning during the indirect test. This should be no surprise if learning occurs for first-order dependencies (as measured by sensitivity to NPP violations) before it occurs for second-order dependencies (measured by sensitivity to NPT violations), that is if participants learn parts of sequences before they learn wholes. Thus, evidence for learning should appear earlier when it is reflected in reaction time differences than when it is reflected in grammaticality judgments because sequence-based grammar learning participants can respond based on partial knowledge of sequences whereas previous research suggests that grammaticality judgments are based on knowledge of larger letter patterns (Gomez & Schvaneveldt, 1994). Additionally, the learning observed for the control group appears to be implicit because direct test performance for these participants failed to differ significantly from performance observed for the direct test controls. These results also suggest that the reaction-time measure used in sequence-based grammar learning is useful for monitoring processing differences in grammatical and nongrammatical sequences.

The experimental group did not differ from the controls for sensitivity to NPP violations, suggesting that implicit learning of first-order dependencies occurs early and improves little, even after six blocks of acquisition. The
experimental group did appear to be learning second-order dependencies during acquisition as manifested by the mean reaction time differences observed for NPT violations. Furthermore, this knowledge appears to be available to awareness, given that letter-same participants significantly outperformed controls on recognition and prediction. Finally, in contrast to Experiment 1, there was no evidence for transfer to a changed letter set in sequence-based grammar learning, suggesting that such learning is specifically tied to surface structure. Interestingly, the absence of transfer in sequence-based grammar learning was accompanied by the failure to observe significant performance on the direct tests.

The differences in the patterns of results between Experiments 1 and 2 suggest that participants are learning more from the holistic presentation of sequences than from a continuous item-by-item presentation. In fact, comparisons of direct test performance in Experiments 1 and 2 lend support to the notion that differential amounts of learning are occurring (see Table 12). When performance was pooled across position of the direct tests, letters-same and letters-different artificial grammar learning participants showed statistically greater deliberate access to memory than did the complementary sequence-based grammar learning groups on every direct test, except for prediction following a bigram in the letters-same condition, \( t(118) = 1.39, p = .168 \), (all other \( t s \geq 4.28 \)). Although deliberate access to memory may not be necessary for exhibiting knowledge of first-order dependencies, such access may factor importantly into more complex learning, such as that involving sensitivity to second-order dependencies and transfer to new surface structure.

**EXPERIMENT 3**

Experiments 1 and 2 assessed the relationship between direct and indirect test performance. Learning of first-order dependencies occurred in sequence-
based grammar learning despite an inability to deliberately access knowledge on the direct tests (control performance in Experiment 2), whereas learning of second order dependencies (in both artificial grammar learning and sequence-based grammar learning) was accompanied by significantly high performance on the direct tests. Although artificial grammar learning participants transferred to a changed letter set, participants in sequence-based grammar learning failed to show transfer. The fact that sequence-based grammar learning groups scored significantly lower than artificial grammar learners on the direct measures, in combination with the fact that sequence-based grammar learning failed to result in transfer, suggests that deliberate access to memory plays an important role in transfer.

The previous experiments assessed knowledge of the acquisition stimuli in relationship to transfer performance. Transfer was accompanied by substantial direct test knowledge of letter patterns in the acquisition stimuli, but in order to understand the mechanisms producing transfer, it is also important to determine how much knowledge participants obtain about patterns in the transfer letter set. Experiment 3 addresses this issue by assessing direct test performance on the transfer materials. If participants show no deliberate access to memory for letter patterns in the transfer set, this would suggest that even though participants can access knowledge of the acquisition set (Experiments 1 and 2), the ability to apply this knowledge during transfer must be implicit.

Method

Participants and Design

The participants were 30 undergraduates at New Mexico State University fulfilling partial requirements for an introductory psychology course. The data from Experiment 1 control participants (the 20 Letter-set 2 direct test controls and 20 indirect test controls), were also used in Experiment 3.

Procedure

The procedure was identical to that used for the transfer group in Experiment 1 who received the direct tests after the indirect test. In Experiment 1, the direct tests were used to assess knowledge for the acquisition materials (Letter-set 2). In Experiment 3, however, the direct tests were used to assess knowledge for the transfer materials (Letter-set 1).

Results and Discussion

First, \( t \) tests were used to determine whether performance on the indirect test exceeded control performance. Discrimination exceeded control performance for NPP violations, \( t(48) = 3.19, p = .003, M = .11, SD = .12 \), \( (M = 0 \text{ and } SD = .12 \text{ for controls}) \), but not for NPT violations, \( t(48) = 0.69, p = .494, M = .03, SD = .19 \), \( (M = 0 \text{ and } SD = .14 \text{ for controls}) \).

Performance was then assessed on the direct tests. Although knowledge of the acquisition materials exceeded control performance in Experiment 1, this was not the case for knowledge of the transfer set. Bigram recognition \( (M = \)
TABLE 13
Mean Recognition Scores for Salient and Frequent Trigrams in the Transfer Letter Set

<table>
<thead>
<tr>
<th>Condition</th>
<th>Transfer group</th>
<th>Direct test controls</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M (SD)</td>
<td>M (SD)</td>
</tr>
<tr>
<td>Beginning trigrams</td>
<td>.14 (.18)*</td>
<td>.02 (.17)</td>
</tr>
<tr>
<td>Ending trigrams</td>
<td>.01 (.19)</td>
<td>.07 (.19)</td>
</tr>
<tr>
<td>Reversals</td>
<td>.11 (.28)</td>
<td>.08 (.26)</td>
</tr>
<tr>
<td>Repetitions</td>
<td>.10 (.26)</td>
<td>.09 (.26)</td>
</tr>
<tr>
<td>Frequent trigrams</td>
<td>.02 (.26)</td>
<td>.16 (.24)</td>
</tr>
</tbody>
</table>

* p ≤ .05.

.14, SD = .22) failed to exceed control performance (M = .10, SD = .14) as did trigram recognition, (M = .07, SD = .17 for experimental participants; and M = .06, SD = .09 for controls). Prediction after bigram presentation (M = .5, SD = .172) also failed to exceed control performance (M = .5, SD = .173), as did prediction after trigram presentation, (M = .44, SD = .11 for experimental participants and M = .41, SD = .10 for controls), all ts ≤ .86, ps ≥ .39.

In addition to evidence that frequent chunks factor importantly in artificial grammar learning (Knowlton & Squire, 1994; 1996), there is also evidence suggesting that salient letter patterns are an important factor (Mathews et al., 1989). It is possible that participants have knowledge of the most frequent or salient letter patterns and use this knowledge in transfer performance, however, the above analysis does not differentiate frequent or salient trigrams from those which are less frequent or salient. Therefore, an additional set of analyses was conducted on the recognition data in order to determine the degree to which salient and frequent letter patterns might be implicated in transfer. Salient patterns were defined to be beginning trigrams, ending trigrams, reversals not occurring in a beginning trigram (e.g., SWS), and any triple with a repetition not occurring in a beginning trigram (e.g., SPP). Beginning and ending trigrams derive their salience by merit of position in a sequence, whereas reversals and trigrams containing repetitions are salient because they contain memorable patterns. Frequent trigrams were defined to be those which were not in the set of salient patterns, but occurred four or more times in an acquisition block (thus 24 or more times during the six blocks of the acquisition phase). Table 13 shows mean recognition performance for salient and frequent patterns in the transfer set. Asterisks are for significant performance on comparisons to the controls.

Knowledge of the transfer set (as assessed by comparisons between the
transfer group in Experiment 3 and the direct test controls) resulted in a significant degree of knowledge for beginning trigrams only, \( t(48) = 2.30, p = .026 \). The experimental group failed to differ from the controls for knowledge of ending trigrams, reversals, trigrams with repetitions, and frequent trigrams not in the set of salient trigrams (ts < 1.86, ps > .07). In order to determine whether the advantage found for knowledge of beginning trigrams was a reflection of salience, frequency, or both, the frequency with which beginning trigrams occurred in the acquisition set was compared to acquisition set frequency for the other trigram categories. If beginning trigrams are more frequent during acquisition than the other patterns, then this might suggest that greater knowledge of beginning trigrams is associated with frequency rather than salience. Mean frequency in the acquisition set was 3.2 occurrences per block for beginning trigrams, 2.4 occurrences for ending trigrams, 2.33 for reversals, 1.75 for trigrams with repetitions, and 4.5 for frequent trigrams not in the set of salient trigrams. Interestingly, the mean frequency of occurrence for initial trigrams was numerically lower than for frequent trigrams, raising the possibility that knowledge of beginning trigrams in the transfer set, relative to the other patterns, is associated with salience rather than frequency.

Although deliberate access to knowledge of letter patterns in the acquisition set was statistically significant, deliberate access to knowledge of letter patterns in the transfer set occurred only for beginning trigrams. Such findings do not rule out the possibility that transfer is based on implicit knowledge of other patterns in the transfer set, but this conclusion seems unlikely given the results of the first two experiments. It is possible that participants are using knowledge of the acquisition set in a strategy to discover legal beginning trigrams in the transfer materials. In the present materials, seven of 15 NPP violations (or 46% of NPP violations) occurred in beginning trigrams. Table 14 shows sensitivity to letter sequences with violations occurring in the beginning trigram, middle, and ending trigram of the test sequences. When sequences were analyzed according to position of the violation, sensitivity to NPP violations failed to exceed control performance for violations occurring in the middle, \( t(48) = 1.91, p = .062 \), or at the end of sequences, \( t(48) = 1.437, p = .157 \). In contrast, violation sensitivity did exceed that of controls when violations occurred in the beginning trigrams, \( t(48) = 2.407, p = .02 \). There were no differences between the experimental group and controls for sensitivity to NPT violations, (ts \( \leq 1.59, ps \geq .088 \)). It is not uncommon for experimenters to use nongrammatical sequences with violations in initial trigrams (e.g., 87% in Experiments 3 and 4 of Altmann et al. [1995], 41–47% in Gomez and Schvaneveldt [1994], and 44% in Knowlton and Squire [1996]). Interestingly, the failure in the present studies to observe significant sensitivity to NPT violations during transfer, as compared to Gomez and Schvaneveldt (1994), may be due to the fact that there was a lower percentage of NPT violations in initial trigrams (20%) as compared to the percentage.
found in Gomez and Schvaneveldt (41%). Until additional research can be conducted, the present findings raise the possibility that the transfer observed in artificial grammar learning simply involves knowledge of initial letter patterns (or simple rules based on noticing such patterns), rather than a complex abstraction mechanism.

### GENERAL DISCUSSION

The premise of the present experiments was that implicit and explicit learning are sensitive to various degrees of complexity and abstractness, ranging from knowledge of first-order dependencies and specific surface structure to second-order dependencies and transfer. These experiments addressed whether implicit learning is sensitive to this entire range of information or whether explicit knowledge becomes an important factor in cases of more complex learning.

Experiments 1 and 2 used the same design and materials, but with two different implicit learning paradigms: artificial grammar learning and sequence-based grammar learning. The motivation for using both approaches was to compare artificial grammar learning to a methodology which discouraged conscious acquisition of letter patterns based on salience and also did not require (or even encourage) participants to access memory for acquisition instances in a deliberate fashion. Participants were tested for deliberate access to knowledge of surface features using direct tests of prediction and recognition. Position of the direct tests was also varied in order to determine its effect on performance.

In Experiment 1 (artificial grammar learning), learning of first-order de-

<table>
<thead>
<tr>
<th>Type and position of violation</th>
<th>Discrimination (P_r)</th>
<th>Transfer group</th>
<th>Indirect test controls</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>M (SD)</td>
<td>M (SD)</td>
</tr>
<tr>
<td>NPP</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>.17 (.17)*</td>
<td>.05 (.16)</td>
<td></td>
</tr>
<tr>
<td>Middle</td>
<td>.09 (.21)</td>
<td>.03 (.25)</td>
<td></td>
</tr>
<tr>
<td>End</td>
<td>.00 (.16)</td>
<td>.07 (.18)</td>
<td></td>
</tr>
<tr>
<td>NPT</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>.13 (.26)</td>
<td>.04 (.20)</td>
<td></td>
</tr>
<tr>
<td>Middle</td>
<td>.09 (.23)</td>
<td>.00 (.17)</td>
<td></td>
</tr>
<tr>
<td>End</td>
<td>.02 (.20)</td>
<td>.00 (.20)</td>
<td></td>
</tr>
</tbody>
</table>

*p ≤ .05.
dependencies, second-order dependencies, and transfer was accompanied by a significant degree of accessibility to knowledge as measured by direct test performance. When participants were grouped according to degree of deliberate access to knowledge, low knowledge participants showed learning of first-order dependencies (as measured by sensitivity to NPP-type violations), but the low knowledge groups failed to show more complex learning, such as learning of second-order dependencies (as measured by sensitivity to NPT violations) or transfer to stimuli with the same underlying rule structure but different surface structure. When more complex learning occurred, it was invariably accompanied by significant performance on the direct tests.

In Experiment 2 (sequence-based grammar learning), learning of first-order dependencies occurred for controls even though this group showed no deliberate access to memory as measured by direct tests. Letters-same participants were not significantly faster than controls on the reaction time measure for learning first-order dependencies, but did outperform controls on the direct measures. This pattern of results suggests that implicit learning of first-order dependencies may occur in the initial stages, however, learners quickly develop the ability to access this knowledge deliberately. Letters-same participants also demonstrated learning of second-order dependencies. Such learning was accompanied by significant direct test performance. Participants in the transfer conditions failed to outperform controls on both direct and indirect tests. The finding that transfer occurred for artificial grammar learning, but not for sequence-based grammar learning, in combination with the finding that participants exhibited significantly greater direct test performance after artificial grammar learning than after sequence-based grammar learning, suggests an important link between deliberate access to memory and transfer.

Experiments 1 and 2 also assessed the position of the direct tests with relationship to the indirect test. Examination of the means in Experiment 1 suggests that some interference may have been produced by taking the direct test before the indirect test in the transfer condition, but interestingly, direct test performance was constant regardless of when such performance was assessed. This result is important because it demonstrates that direct knowledge can be accurately assessed after the grammaticality task, even in transfer conditions. Position of the direct test had no effect on the reaction time measure used in Experiment 2, and direct test performance did not change significantly with exposure to the indirect test.

Experiments 1 and 2 investigated deliberate access to knowledge of letter patterns in the acquisition set. However, in order to learn more about transfer, Experiment 3 investigated access to knowledge of letter patterns in the transfer letter set. It was reasoned that if generalization from knowledge of acquisition items is implicit, then participants should have no deliberate access to knowledge of letter patterns in the transfer letter set. If participants were to show such access, then this would suggest that some aspect of the relationship between the acquisition and transfer items is either explicitly represented in
memory or is abstractable at test (e.g. Redington & Chater, 1996). Fine-grained analyses of salient triples and frequent triples showed that knowledge of the transfer set occurred for beginning trigrams. Beginning trigrams occurred less often than frequent trigrams, suggesting that the advantage observed for beginning trigrams might be due to salience of position, rather than frequency. Furthermore, when indirect test performance was evaluated for sequences with initial trigram violations only, violation sensitivity exceeded that of controls. In contrast, experimental participants performed no differently than controls when violations occurred in the middle or ending portions of sequences.

Taken together, these experiments suggest that implicit learning occurs only at the simplest level of complexity (i.e., for first-order dependencies), but even in simple cases, implicit and explicit learning appear to be highly associated. Moreover, explicit learning appears to be an important factor in cases of greater complexity (such as that involved in learning second-order dependencies and transfer).

Transfer in Amnesic Patients

Recently, Knowlton and Squire (1996) demonstrated transfer to a changed letter set using a group of amnesic patients. Because these same patients were unable to discriminate legal from illegal bigrams and trigrams on a recognition test, Knowlton and Squire concluded that the knowledge of letter patterns underlying grammaticality performance must be nondeclarative (or implicit). Thus, according to Knowlton and Squire, any explicit knowledge of letter patterns observed in normal populations must be epiphenomenal to grammaticality performance. Although Knowlton and Squire’s (1996) results seem to contradict those of the present experiments, a discussion of methodological differences may resolve the apparent inconsistencies.

One methodological problem with the results reported by Knowlton and Squire (1996), is that grammaticality performance is compared to chance rather than to controls who perform grammaticality judgments without the benefit of participating in the study phase. Comparisons to controls are important for eliminating the possibility that test performance is merely reflecting learning on the test or any other factors that may be contributing to test performance. The use of controls has been advocated by more than one implicit learning researcher (e.g., Perruchet, 1994; Redington & Chater, 1996) and is becoming a matter of practice in artificial grammar learning research (Altmann et al., 1995; Mathews et al., 1989; Perruchet & Pacteau, 1990; St. John & Shanks, in press). For that matter, sometimes control performance exceeds chance (e.g., Dulany et al., 1984) observed mean control performance at 56% correct.

It is possible to compare certain aspects of the Knowlton and Squire (1996) results with those reported in the present experiments. Knowlton and Squire isolated violations of first-order dependencies and second-order dependencies
in their Experiment 1, referring to these as chunk and location violations. Knowlton and Squire were primarily interested in comparing chunk and location violations to each other, and thus did not report above baseline significance levels for these violations separately. However, discrimination scores can be approximated from their results in order to examine how patient group performance compares to that observed in the present experiments. Although sensitivity to NPP violations was robust in the Knowlton and Squire data (.24), sensitivity to NPT violations in their experiment (.09) was low compared to the present experiments (.13 and .14). Transfer performance was also low, with mean percent correct ranging from 54.6 to 57.3 (it was impossible to compute discrimination in this case because separate scores were not reported for grammatical and nongrammatical items). The fact that Knowlton and Squire reported a statistical trend for lower transfer performance for amnesics compared to normal individuals also raises some question concerning the nature of the performance observed. It could well be the case that amnesics would show the pattern of learning observed in the present studies (where implicit learning occurs only in the cases of least complexity) when appropriate controls are used.

If amnesics do show learning of greater complexity when appropriate baseline controls are used, then it is important to examine the possibility that this performance is based on declarative knowledge of salient letter patterns. Recall that participants in Experiment 3 of the present studies failed to exceed control performance on general recognition for bigrams and trigrams in the transfer set, but still showed above control performance for knowledge of beginning trigrams. Discrimination on the indirect test was also greatest for violations occurring in beginning trigrams. Given the declarative memory impairments suffered by amnesics, it may be the case that these patients access fewer bigrams and trigrams than normal participants, but enough particularly salient letter patterns to support grammaticality performance. If so, then discrimination for legal versus illegal chunks might be observed in a fine-grained analysis of the Knowlton and Squire (1996) data.

On Comparing Sequence-Based Grammar Learning to Serial Reaction Time Learning

Most research on learning of second-order dependencies has been conducted using the SRT learning paradigm. Given the methodological differences between sequence-based grammar learning and SRT learning, it is important to relate the present findings, especially those suggesting that learning of second-order dependencies is linked with explicit knowledge, to those previously reported in the SRT learning literature. Previous research shows mixed conclusions. Cohen et al. (1990) found that participants were unable to learn second-order dependencies under dual-task conditions, suggesting that awareness is involved in learning such contingencies. Consistent with this view, Perruchet and Amorim (1992) found that implicit and explicit learning were highly associated in SRT learning. In contrast, Cleeremans
and McClelland (1991) and Jimenez, Mendez, and Cleeremans (1996) found evidence for SRT learning of second-order dependencies on sequences generated from an artificial grammar, however, such learning was not related to direct test performance.

Perhaps the biggest difference in traditional sequence learning paradigms and sequence-based grammar learning is in the visual presentation of stimuli. Participants in the former track the location of a target, but in the latter all spatial information is lost (in sequence-based grammar learning one letter appeared in the center of the screen and was then replaced by the next letter in sequence). It could be that spatial location provides cues to second-order dependencies, but such knowledge may lend itself more naturally to an implicit mechanism, one which does not represent knowledge in terms of verbalizable patterns or rules. Withholding spatial cues from participants in Experiment 2 may have forced them to rely on the only cues available, namely those resulting from chunking runs of adjacent letters. Such knowledge may be more verbalizable than the spatial pattern of sequence locations participants are exposed to in serial reaction time learning.

One other difference between Experiment 2 and Cleeremans’ studies may account for the differences observed. Subjects in Experiment 2 participated in fewer trials (720 acquisition transitions and 465 test transitions over a period of one session) than subjects in Cleeremans and McClelland (1991) and Jimenez et al. (1996) (who participated in approximately 60,000 transitions over a period of 20 sessions). Given that Perruchet and Amorim (1992) also found a relationship between implicit and explicit learning after short acquisition, it is conceivable that the relationship between explicit and implicit knowledge may be different at 1200 as compared to 60,000 training trials. This difference raises interesting questions concerning the relative time-course of implicit and explicit learning. For example, perhaps explicit knowledge plays some role in learning second-order contingencies early on, but becomes unnecessary after extended practice. Such a pattern would be consistent with the idea that declarative knowledge becomes compiled and unavailable to awareness with sufficient training (Anderson, 1987).

On Finding Transfer in Sequence-Based Grammar Learning

One question that might also be raised is why one should expect to find transfer in sequence-based grammar learning given that learning is acquired in the context of a heavily response- and motor-based task. In other words, why should one expect the motor programs resulting from learning in one letter set to transfer to an entirely new letter set? For instance, if one learns to type ‘‘M-M-X’’ why would we expect transfer to ‘‘W-W-Z’’? Furthermore, even if participants noticed the repetition in the example above (or in an example such as ‘‘N-P-N-P-Z’’), then that knowledge should not show up in reactions times because the specific motor commands would have to be trained in the new letter set.
In fact, several sources of evidence suggest that the locus of SRT learning is not entirely response based. First, participants can transfer easily to different effectors. For instance, participants who learned a sequence using two fingers showed no decrements in response time when they had to respond to the sequence with four fingers (Stadler, 1989). Participants were also able to transfer between arm and finger responses and from finger to vocal responses (Keele et al., 1995).

Second, SRT learning occurs independently of the system which selects responses. Howard et al. (1992) transferred participants to sequential responding after exposure to the sequence either by observation or by responding to the sequential pattern (as in standard SRT learning). Participants performed as well after observation as they did after sequential responding as reflected in comparable performance in the standard SRT task.

Third, Mayr (1996) found evidence for acquisition of both spatial and nonspatial regularities in SRT learning. Mayr trained participants on two independent, but simultaneously presented, sequences (one object-response based and the other spatially based). One source of sequential information was realized in the response to object cues (such as black or white squares and circles), where type of object occurred according to a sequence, but was presented indeterminately in one of four locations on the screen. The other source of sequential information was realized in the spatial location of objects (it should be emphasized that the object and location sequences were entirely independent). Performance was disrupted as much when the spatial sequence became random as when the object sequence became random, demonstrating that in addition to learning the response-based sequence, participants were also learning the spatial sequence. These results are important because they suggest that SRT learning takes place at a higher level of representation than merely at the level of motor-based programs.

Finally, given that participants were indeed learning second-order dependencies in Experiment 2, there is no reason not to expect transfer unless transfer is linked to explicit knowledge. That is, given that virtually all ambiguities in the present grammar can be resolved with knowledge of second-order dependencies, such knowledge should in theory be sufficient for supporting transfer. Participants in both experiments showed second-order dependency learning, but sequence-based grammar learning did not result in transfer. Given that the most prevalent difference between Experiments 1 and 2 was the high level of explicit knowledge found in the former and not in the latter, this pattern of results points to deliberate access to knowledge of letter patterns as an important source of information in transfer.

**Process Dissociation**

It should be noted that there is, in fact, a great deal of controversy regarding the classification of implicit and explicit tasks and the problems which arise from the practice of equating processes with tasks (Jacoby, Yonelias, 

Toth, 1993). Jacoby et al. (1993) argue that showing a dissociation between performance on direct and indirect tests can be misleading because explicit tests actually underestimate the contribution of unconscious processes. The fact that implicit performance can underestimate the contribution of explicit processes has been debated for some time (e.g. see Holender, 1986, for a discussion of this issue in the context of subliminal perception). The process-dissociation approach advocated by Jacoby et al. identifies intentional (explicit) and nonintentional (implicit) processes within a single task in order to better separate the relative contributions of each. The advantage of such an approach is that it deals directly with the relative impact of intentional and nonintentional processes rather than ignoring them, as is often done when processes are arbitrarily defined in terms of tasks.

The objective of the present experiments was to compare and contrast tasks commonly used in implicit learning research in order to better determine the relationships between these tasks. An advantage of relying on methodologies with a precedent of use is that experimental outcomes can be evaluated within the context of prior research. Additionally, some of the fundamental assumptions underlying the process dissociation approach have been recently contested (e.g., Curran & Hintzman, 1995; Dodson & Johnson, 1996; Komatsu, Graf, & Uttl, 1995). However, the argument advanced by Jacoby, et al. is still an important one to take seriously.

Process dissociation is based on the assumption that conscious, intentional processes and automatic, nonintentional processes act together during recollection. In an effort to factor out the influence of nonintentional processes, Jacoby et al. (1993) used two “opposing” conditions in assessing recollection. In the inclusion condition, participants were instructed to complete word stems with words they remembered from previous exposure to a study list. In the exclusion condition, participants were asked to complete word stems with words that were not present in the study list. Using this approach, recollection (or intentional control) was measured as the difference between when participants were “trying to” versus “trying not to” engage in an act. Jacoby et al. argued that when participants are instructed to complete a task with information presented earlier, both conscious and unconscious influences should lead to an increase in performance, but when participants are instructed to complete a task with information not presented earlier, conscious remembering should inhibit the use of previously presented information. Thus, any intrusions of previously presented information must be due to the unconscious influence of memory.

In a preliminary investigation of this approach, students at New Mexico State were exposed to a grammar and then made grammaticality judgments in the same manner as in Experiment 1. Participants then performed the prediction task under inclusion and exclusion conditions. Participants showed a very low proportion of intrusions on the exclusion task, suggesting substantial deliberate control over the use of their knowledge. The proportion of legal
completions in the exclusion condition was subtracted from the proportion of legal completions in the inclusion condition in order to obtain a more conservative estimate of direct knowledge (compared to the measures used in Experiments 1 and 2). Even with the more conservative recollection estimate, performance statistically exceeded estimated guessing. Approximately 50% of the participants performed perfectly on some aspect of the exclusion task (i.e., successfully made only illegal completions following presentation of a single letter, bigram, or trigram), thus making it impossible to compute a measure reflecting the unintentional use of memory. (Jacoby et al.’s [1993] automatic measure of memory is undefined when inclusion is perfect and is underestimated when exclusion is perfect.) However, the fact that participants showed such a high degree of intentional control under exclusion conditions can be taken as additional evidence for access to explicit knowledge in artificial grammar learning.

Mechanisms of Learning

Given that some learning mechanisms acquire simple, specific information and other learning mechanisms acquire more complex, general information, it is important to assess these findings in terms of the models outlined in the Introduction.

Although the approach advocated by Servan-Schreiber and Anderson (1990) accounts for learning of first-order and second-order dependencies (see Table 1), one constraint of the model is that chunks are tied to specific surface features of the acquisition materials, thus making it impossible for the model to accommodate transfer. Additionally, this model predicts learning driven by frequency rather than salience of chunks. Finally, according to competitive chunking theory, participants have deliberate access to memory for chunks, but the relationships among chunks are implicit in nesting structure and chunk strength. By this view, chunk strength gives rise to feelings of familiarity, which in turn, influence grammaticality judgments. In an empirical test of this model, Buchner (1994) found familiarity effects, but these were not significantly related to grammaticality performance, raising the possibility that application of knowledge retrieved via memory search might indeed be contributing to performance. The present results support Buchner’s hypothesis by establishing the presence of substantial access to memory of bigrams and trigrams.

The recurrent networks proposed by Cleeremans and McClelland (1991) and Dienes et al. (1995) accommodate learning of first-order dependencies and second-order dependencies. Furthermore, the model proposed by Dienes et al. accommodates transfer. Additionally, the models successfully predict human SRT performance (Cleeremans & McClelland, 1991) and grammaticality performance (Altmann et al., 1996). However, there is no mechanism in these models for learning rules involving salient letter patterns. Instead, transfer is accomplished via an implicit mapping between acquisition and test
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domains. These models also predict that very frequent regularities should be better learned than less frequent regularities.

First, evidence supporting the idea that transfer requires an abstract mapping between letter sets or domains is still inconclusive. Altmann et al. (1995) argued that abstract rules involving repetitions or alternations could not be the only mechanism underlying transfer, that is, learning the mapping between letter sets must also be a factor. In support of this view, Altmann et al. removed all grammatical and nongrammatical items containing alternations from their analyses and showed that transfer performance was still significant. However, Altmann et al. did not remove nongrammatical sequences beginning with illegal letters from these analyses, raising the possibility that the residual transfer effect was simply due to judging sequences starting with low-frequency letters as nongrammatical. Although grammaticality judgments on sequences beginning with illegal letters could involve mapping between initial letters in the acquisition and test domain, such transfer is much less interesting than when participants learn a mapping for all the letters.

Second, according to the model proposed by Dienes et al., the mapping between letter sets should also be implicit. There is only one study investigating whether participants have deliberate access to the mapping between letter sets. Manza and Reber (1996) required participants to match letters from the acquisition and transfer sets after artificial grammar learning. Participants failed to learn the mappings between letter sets in two cases (Experiments 2 and 5), but showed a significant degree of knowledge of letter mappings in another case (Experiment 6).

Third, participants in Experiment 3 showed a significant degree of access to beginning trigrams compared to frequent trigrams in the transfer set even though the frequency of occurrence for beginning trigrams was lower than for frequent trigrams. Additionally, violations in initial trigrams appeared to factor importantly in transfer, suggesting a link between deliberate access to initial trigrams and grammaticality performance. Findings such as these raise the possibility that salient regularities play an important role in transfer.

Finally, Dienes et al. (1995) predicts that more successful processing of grammatical compared to nongrammatical sequences should underlie grammaticality performance. According to this view, knowledge is realized in the pattern of activation stored in the hidden units, and thus, deliberate access to specific knowledge is not central to grammaticality judgments. Slower processing was found for sequences with violations of first- and second-order dependencies using sequence-based grammar learning, but processing differences were not observed in the case of transfer. Furthermore, participants did appear to have substantial access to specific knowledge and when such access was absent, there was a failure to observe transfer.

Given that participants in the present studies exhibited deliberate access to knowledge of letter patterns, it is important to understand how such knowledge might be realized in connectionist models such as those pro-
posed by Cleeremans and McClelland (1991) and Dienes et al. (1995). One interpretation of the learning represented in connectionist models is that weights embedded inside the learning mechanism are not available to introspection, and hence must be implicit (Cleeremans, 1993). According to a proposal advanced by St. John and Shanks (in press) if the effects of weights are felt during performance in terms of more certain responses for fragments or patterns with greater weights and less certain responses associated with weaker weights, then participants might be able to report verbal knowledge associated with stronger responses. On this view, awareness is epiphenomenal to performance. However, regardless of how people come to have deliberate access to memory, once this access is accomplished, it seems plausible that such knowledge could be used to enhance performance by feeding back into the model in the form of a top-down mechanism. The models proposed by Cleeremans and McClelland (1991) and Dienes et al. contain no such mechanism.

The Redington and Chater (1996) proposal suggests that instead of being stored in an abstract form, perhaps the information necessary for grammaticality performance is abstractable from specific knowledge of letter patterns at test. According to this view, knowledge of letter patterns is accessed via deliberate memory search and is subsequently matched against the target sequence at test. As a demonstration of this hypothesis, Redington and Chater constructed simple models which use surface features of the acquisition sequences to make grammaticality judgments. According to these models, knowledge of bigrams was sufficient for predicting sensitivity to NPP violations in the Gomez and Schvaneveldt (1994) data, but knowledge of trigrams was important for predicting sensitivity to NPT violations and transfer. Furthermore, when the stimuli used in the present studies were subjected to the Redington and Chater models, all models predicted above chance performance on NPP violations in the same letter set, but only trigram sensitive models predicted above chance performance on NPT violations or on transfer to a changed letter set (Redington, personal communication).

The models proposed by Redington and Chater (1996) provide a plausible account of grammaticality performance based on access to specific information (rather than one based on processing differences). Furthermore, these models find empirical support in the present experiments. However, it is important to note that these models do not address how learning initially takes place. Thus, a more complete account of artificial grammar learning would interface a learning mechanism with retrieval processes such as those proposed by Redington and Chater.

Finally, the kinds of rules embodied in THIYOS (Druhan & Mathews, 1989; Mathews, 1991; Roussel, Mathews, & Druhan, 1990) can certainly account for learning of first- and second-order dependencies based on positional knowledge of letter fragments. The behavior predicted by this model
is also consistent with the transfer performance observed in the present studies, but does not address transfer which requires a mapping between letter sets. The ability participants show for accessing their knowledge on direct tests is also consistent with the relationship between verbalizable and nonverbalizable knowledge in THIYOS and predicts that if explicit processes alter the set of rules controlling behavior, then participants should have access to these rules. By this view, participants are aware of salient or frequent letter fragments during learning and can express these patterns in the form of rules, but the relative strength of rules is adjusted implicitly.

One drawback of THIYOS is that it was designed to model a more extended, analytic learning process than the observation and memorization to criterion procedures typically used during artificial grammar learning. In particular, subjects participated in extended learning sessions (involving 200 trials), in which their task was to select a grammatical target from a list of five possibilities (only one of which was grammatical). It would seem that simultaneous presentation of legal and illegal sequences and the subsequent comparisons involved in making grammaticality judgments could greatly raise potential for implicit feedback. Additionally, some participants received explicit feedback, input which must factor importantly into the process by which the relative strength of rules is adjusted in the system. Given that acquisition and test trials are normally small in number, it is not clear whether participants in typical artificial grammar learning studies obtain sufficient exposure for rule strength to be adjusted by the system. Therefore, although the predictions of this model are consistent with the results obtained in the present studies, models that incorporate the constraints of the tasks actually used during artificial grammar learning might more accurately represent the learning process.

In summary, both competitive chunking theory (Servan-Schreiber & Anderson, 1990) and the recurrent network proposed by Cleeremans and McClelland (1991) represent learning of first- and second-order dependencies; however, neither are capable of representing transfer. The model proposed by Dienes et al. (1995) is essentially an associative network, and thus clearly embodies knowledge of first-order associations. Furthermore, this model can account for learning of second-order dependencies and transfer, but does not account for transfer performance involving salient letter patterns. Neither does this model have a mechanism for representing the top-down influence that explicit knowledge might have on the system. THIYOS, advocated by Mathews and colleagues is capable of learning all levels of complexity and can also support learning of both salient and frequent letter patterns, but it is not clear how this model would perform in the context of the short acquisition and testing phases characteristic of most artificial grammar learning experiments. However, an important aspect of THIYOS is the representation of rules based on salient letter patterns. Such rules may factor importantly into transfer performance. Although participants showed little access to reversals and repetitions in the transfer letter set, they did show substantial access to beginning
trigrams. Furthermore, beginning trigrams were linked to grammaticality perfor-

mance.

The models proposed by Redington and Chater (1996) are consistent with the fact that participants exhibit substantial knowledge of specific letter patterns and letter fragments. However, the finding that participants showed implicit learning of first-order contingencies in the absence of deliberate access to specific knowledge raises the question of whether distinct mechanisms for implicit and explicit access to knowledge should be implemented in these models. Furthermore, there is no mechanism in the Redington and Chater models for explaining how learning initially occurs. Thus, their models may be more appropriate for representing the apparent link between access to specific knowledge and grammaticality judgments.

If implicit learning is ultimately frequency rather than salience based, then models, such as those proposed by Cleeremans and McClelland (1991), Dienes et al. (1995), or Servan-Schreiber and Anderson (1990) may be more appropriate for representing the process by which learning occurs, as well as the basis for the first-order dependency learning evidenced by low knowledge participants in Experiment 1 and control participants in Experiment 2. On this view, a plausible account of implicit learning might involve a learning mechanism which is then permeable to search and retrieval processes, such as those described by Redington and Chater. It might also be important in an account such as this to specify how top-down processing might be realized during learning. If future research shows that salient letter patterns enjoy a special status during learning, then the learning mechanism would clearly have to reflect this status.

There are two issues in need of additional research. One issue involves the role of salience versus frequency in implicit learning. Presumably, frequency-based learning is more consistent with an implicit learning mechanism, whereas learning based on salience of letter patterns assumes some awareness of or deliberate access to these patterns. The present results suggest that salience might be involved in transfer, but salience and frequency were not manipulated orthogonally, thus additional research is clearly necessary for investigating this claim. A second issue is whether transfer involves a mapping mechanism or the use of rules. The models proposed by Redington and Chater (1996) emphasize a view of transfer in which participants use specific knowledge to infer the mapping between acquisition and transfer sets. According to the model proposed by Dienes et al. (1995), transfer is accomplished by an abstract mapping between the

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6 Buchner (1994) advanced a similar proposal with regard to adding search and retrieval processes to competitive chunking theory. However, Buchner did not specify how knowledge resulting from search and retrieval processes might result in grammaticality judgments.
acquisition and transfer domains. In contrast, Mathews and colleagues (Druhan & Mathews, 1989; Mathews, 1991; Roussel et al., 1990), propose that transfer is not accomplished via a mapping between acquisition and transfer domains, but rather by application of rules involving repetitions and alternations. Deciding this issue is important for deciding on the most appropriate learning mechanism. For instance, if all transfer is based on rules or abstraction from knowledge of specific letter patterns, then this might eliminate the need for an abstract mapping between acquisition and transfer domains, such as the one proposed by Dienes et al. (1995). The issues of salience- versus frequency-based learning and whether transfer does or does not involve mapping cannot be decided on the basis of the present experiments (or based on the current literature), therefore additional research is needed for deciding these issues.

Perhaps the most important message to obtain from the present experiments is that instead of being abstract and complex, implicit learning appears to be primarily associated with learning of first-order dependencies. More complex cases of learning, such as those involved in learning second-order dependencies and transfer appear to be associated with deliberate access to memory. Such findings have implications for the complexity with which researchers view implicit learning, as well as details of the mechanisms postulated in implicit learning theory.

REFERENCES


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