INFORMATION TO USERS

This manuscript has been reproduced from the microfilm master. UMI films the text directly from the original or copy submitted. Thus, some thesis and dissertation copies are in typewriter face, while others may be from any type of computer printer.

The quality of this reproduction is dependent upon the quality of the copy submitted. Broken or indistinct print, colored or poor quality illustrations and photographs, print bleedthrough, substandard margins, and improper alignment can adversely affect reproduction.

In the unlikely event that the author did not send UMI a complete manuscript and there are missing pages, these will be noted. Also, if unauthorized copyright material had to be removed, a note will indicate the deletion.

Oversize materials (e.g., maps, drawings, charts) are reproduced by sectioning the original, beginning at the upper left-hand corner and continuing from left to right in equal sections with small overlaps. Each original is also photographed in one exposure and is included in reduced form at the back of the book.

Photographs included in the original manuscript have been reproduced xerographically in this copy. Higher quality 6” x 9” black and white photographic prints are available for any photographs or illustrations appearing in this copy for an additional charge. Contact UMI directly to order.

UMI
A Bell & Howell Information Company
300 North Zeeb Road, Ann Arbor MI 48106-1346 USA
313/761-4700   800/521-0600
RICE UNIVERSITY

IMPLICIT LEARNING IN VISUAL SEARCH:
IMPLICATIONS FOR
COMPLEX TASK PERFORMANCE

by

KELLY NEVILLE

A THESIS SUBMITTED
IN PARTIAL FULFILLMENT OF THE
REQUIRED FOR THE DEGREE
DOCTOR OF PHILOSOPHY

APPROVED, THESIS COMMITTEE:

Addie Ehrenstein
Addie Ehrenstein, Assistant Professor, Director
Psychology

Bruce Etynre
Bruce Etynre, Associate Professor
Human Performance and Health Sciences

David Lane, Associate Professor
Psychology

Samuel Schiflett
Samuel Schiflett, Senior Research Psychologist
Sustained Operations Branch, Armstrong
Laboratory, United States Air Force

Michael Watkins, Professor
Psychology

Houston, Texas
May, 1996
Abstract

Implicit Learning in Visual Search: Implications for Complex Task Performance

by

Kelly Neville

Implicit learning, defined here as learning without intention, was demonstrated during the performance of a search task, thereby extending the finding of implicit learning in relatively simple tasks. Implicit learning was primarily limited to unique associations in a target feature sequence (i.e., associations in which a particular element is always followed by the same element, as 2 follows 1 in the sequence 125124). Implicit learning was similar under both distributed and focused visual attention and was unaffected by added workload, indicating that implicit learning utilized minimal attentional resources. In contrast, when subjects were instructed to learn the sequence (i.e., were to use an explicit learning mode), sequence learning was adversely affected by added workload, and the impairment was similar for both unique and ambiguous associations. Implicit learning in a distributed-attention search task was similar to implicit learning in a simpler serial reaction time task. However, in a focused-attention search task that was more perceptually-demanding, sequence learning benefits did not appear until late in task performance. This pattern suggests that implicitly-learned sequence information may have been retrieved and used only after becoming explicit. This research also demonstrated that associations
between sequence elements are not learned implicitly if a sequenced stimulus feature is not assigned to responses. This indicates that associations between stimulus-response pairs, but not between stimuli alone, were learned. In addition to ambiguous sequence associations, high perceptual demands, and the absence of response assignments for patterned stimuli, low accuracy rates, low event rates, and cumbersome response codes were implicated as potential sources of interference in implicit learning. An instance-based model of implicit learning is indirectly supported, according to which implicit learning benefits reflect the storage and subsequent activation (i.e., retrieval) of instances that contain response-relevant stimulus information, the response, and information about the next event or immediate consequence of that response.
Acknowledgements

I am particularly grateful to my advisor, Addie Ehrenstein, for her guidance in this project and for all that I learned from her in the process of completing it. I am also grateful for the constant support and encouragement I received from the Sustained Operations Laboratory (AL/CFTO) at Brooks Air Force Base (BAFB) and, in particular, from my assigned mentor, Sam Schiflett, my supervisor, Bill Storm, and my co-worker and husband, Jon French, who in addition to being helpful and supportive, patiently endured our weekly separations for almost three years. I am indebted to my parents, Steve and Sue Neville, who encouraged me to obtain a good education so that I may successfully pursue my goals and dreams, and who have been unconditionally proud of me every step of the way. I also wish to acknowledge the Department of Psychology of Rice University for the education they have provided and AL/CFTO for lessons on respect, responsibility and professionalism. Finally, I would like to acknowledge the U.S. Air Force for its financial support of my graduate education.
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Introduction</td>
<td>1</td>
</tr>
<tr>
<td>Characteristics of Implicit Learning</td>
<td>4</td>
</tr>
<tr>
<td>Can Learning With Awareness Be Implicit?</td>
<td>6</td>
</tr>
<tr>
<td>Attentional Requirements of Implicit Learning</td>
<td>8</td>
</tr>
<tr>
<td>Can Complex Relations Be Learned Implicitly?</td>
<td>10</td>
</tr>
<tr>
<td>The Relationship of Implicit Learning to Explicit Learning</td>
<td>11</td>
</tr>
<tr>
<td>The Relationship of Implicit Learning to Implicit Memory</td>
<td>12</td>
</tr>
<tr>
<td>Implicit Learning Paradigms</td>
<td>14</td>
</tr>
<tr>
<td>Contributions of Artificial Grammar Learning Studies</td>
<td>15</td>
</tr>
<tr>
<td>Contributions of Control of Dynamic Systems Studies</td>
<td>16</td>
</tr>
<tr>
<td>Contributions of Sequence Learning Studies</td>
<td>18</td>
</tr>
<tr>
<td>Summary of Results of Implicit Learning Studies</td>
<td>20</td>
</tr>
<tr>
<td>Possible Loci of Implicit Learning</td>
<td>21</td>
</tr>
<tr>
<td>Perceptual Processes as a Possible Locus of Implicit Learning</td>
<td>22</td>
</tr>
<tr>
<td>Central Processes as a Possible Locus of Implicit Learning</td>
<td>24</td>
</tr>
<tr>
<td>Motoric Processes as a Possible Locus of Implicit Learning</td>
<td>24</td>
</tr>
<tr>
<td>Conclusions About the Loci of Implicit Learning</td>
<td>25</td>
</tr>
<tr>
<td>Implicit Learning During Complex Task Performance</td>
<td>27</td>
</tr>
</tbody>
</table>
The Effects of Multiple-Task Demands on Implicit Learning 28

Effects of Secondary Tasks on Implicit Learning 28

Effects of Secondary Tasks on Attention 29

Interference by Secondary Tasks not Related to Attention 31

Perceptual Demands and Their Effects on Implicit Learning 33

Varieties of Visual Attention 33

Implicit Learning Under Distributed-Attention Conditions 34

Interactive Effects of Visual Attention and Mental Workload on Implicit Learning 38

Overview of Present Experiments 39

Experiment 1 41

Experiment 1a 44

Method 44

Results and Discussion 52

Sequence Learning 53

Unique and Ambiguous-Association Learning 55

The Effects of Search Task Accuracy on Sequence Learning 57

The Relationship Between Secondary Task Performance and Sequence Learning 61
The Relationship Between Explicit Knowledge and Sequence Learning 62
Search Task Learning 68
Set-Size Effects on Search Task Performance 69
Summary of Experiment 1a Results 72
Analysis of Visual Attention Strategies 74

Experiment 1b 80

Method 81

Results and Discussion 82

Sequence Learning 82

Unique and Ambiguous-Association Learning 86

The Effects of Search Task Accuracy on Sequence Learning 88

The Relationship Between Secondary Task Performance and Sequence Learning 89

The Relationship Between Explicit Knowledge and Sequence Learning 89

Search Task Learning 93

Set-Size Effects on Search Task Performance 94

Summary of Experiment 1b Results 95

Experiment 1c 97

Method 98

Results and Discussion 101
Sequence and Association Learning 101
Search Task Performance Effects on Sequence Learning 105
Search Task Learning 106
Set-Size Effects on Search Task Performance 107
Summary of Experiment 1c Results 107
Analysis of Visual Attention Strategy 109
Experiment 1d 110
Method 110
Results and Discussion 111
Sequence Learning 112
The Effects of Search Task Accuracy on Sequence Learning 112
Search Task Learning 114
Summary of Experiment 1d Results 114
Experiment 2 115
Method 116
Results and Discussion 119
Sequence and Association Learning 120
Search Task Learning 124
Summary of Experiment 2 Results 125
General Discussion 126
Limits of Implicit Learning 127

Effects of Accuracy Rate on Sequence Learning 128

Effects of Response Code Complexity on Sequence Learning 130

Effects of Event Intervals on Sequence Learning 130

Effects of Sequence Structure Complexity on Sequence Learning 131

Effects of Intention on Learning Different Types of Sequence Associations 131

Effects of Performance Demands on Sequence Learning 134

Implicit Sequence Learning Loci and Mechanisms 134

Potential Applications 136

Future Directions 138

References 141

Appendices 154
List of Figures

Figure 1. A display like those in the narrow-focus condition of Experiment 1a. 46

Figure 2. A display like those in the wide-focus condition of Experiment 1a. 47

Figure 3. Mean reaction time (in ms) as a function of block under different perceptual requirement and workload conditions in Experiment 1a. 56

Figure 4. Mean reaction time (in ms) as a function of block for knowledge and no-knowledge groups under single-task and dual-task workload conditions in Experiment 1a. 66

Figure 5. Mean reaction time (in ms) as a function of block under different workload and instruction conditions in Experiment 1b. 85

Figure 6. Mean reaction time (in ms) as a function of block for knowledge and no-knowledge groups of subjects instructed to learn explicitly under single-task and dual-task workload conditions in Experiment 1b. 92

Figure 7. A display like those in Experiment 1c. 99

Figure 8. Mean reaction time (in ms) as a function of block for all sequence associations and for unique associations during search task performance in Experiment 1c. 104

Figure 9. Mean reaction time (in ms) as a function of block for low and high accuracy groups of subjects in Experiment 1d. 113

Figure 10. A display like those in Experiment 2. 117

Figure 11. Mean reaction time (in ms) as a function of block for unique associations in each between-subject condition of Experiment 2. 122
List of Tables

Table 1. Mean increases in reaction time (in ms) from Block 5 to Block 6 for different types of sequence associations in Experiment 1a. 53

Table 2. Mean increases in percent errors from Block 5 to Block 6 for different types of sequence associations in Experiment 1a. 54

Table 3. Mean increases in reaction time (in ms) and percent errors between Blocks 5 and 6 for groups of high-accuracy and low-accuracy subjects in Experiment 1a. 57

Table 4. Mean explicit knowledge scores and reaction time increases (in ms) between Blocks 5 and 6 for different learner groups in Experiment 1a. 64

Table 5. Mean increases in reaction time (in ms) from Block 5 to Block 6 for different types of sequence associations in Experiment 1b. 83

Table 6. Mean increases in percent errors from Block 5 to Block 6 for different types of sequence associations in Experiment 1b. 84

Table 7. Mean explicit knowledge scores and reaction time increases (in ms) between Blocks 5 and 6 for different learner groups in Experiment 1b. 90

Table 8. Mean increases in reaction time (in ms) and percent errors from Block 7 to Block 8 for different types of sequence associations in Experiment 1c. 102

Table 9. Mean increases in reaction time (in ms) from Block 5 to Block 6 for different types of sequence associations in Experiment 2. 120

Table 10. Mean increases in percent errors from Block 5 to Block 6 for different types of sequence associations in Experiment 2. 123
Implicit Learning in Visual Search:  
Implications for Complex Task Performance

Implicit learning, defined here as unintentional learning that occurs as a byproduct of repeated exposure to patterns in the task environment, is a means of learning information that might not be learned intentionally for reasons that include a lack of awareness of its potential value and high task demands that spare few cognitive resources. Consequently, implicit learning may be an important mechanism for improving performance and acquiring expertise, especially during performance of complex tasks with high cognitive demands or high information loads that interfere with the explicit recognition of important variables. For example, a fighter pilot may be too busy to analyze the attack strategy used by an opposing squadron, but through repeated engagements he or she might implicitly learn to anticipate its moves. Implicit learning may also represent a mode of learning that requires little or no attention (e.g., Curran & Keele, 1993; Seger, 1994; Stadler, 1995) and that is resistant to stress (e.g., Masters, 1992). Such qualities would render it especially valuable in environments with high processing demands and performance pressure. In fact, implicit learning may be specialized for complex environments (e.g., Berry & Broadbent, 1988; Hayes & Broadbent, 1988; Lewicki, Hill, & Czyzewska, 1992; Seger, 1994).

In complex operational environments, a single wrong decision or slow response can have huge repercussions. The use of implicitly learned patterns in task performance could improve performance
significantly and also help prevent serious accidents. Implicit learning also might be of value to complex task performance by facilitating time-pressured decision making. To make decisions under pressure, people may use a decision-priming (e.g., Klein, 1993) or intuitive (e.g., Hammond, Hamm, Grassia, & Pearson, 1987) process. Klein (1993) hypothesizes that under time pressure, experts process relevant perceptual cues and situational variables which, in turn, prime a feasible decision that is evaluated using mental simulation. Thus, a decision is primed, rather than selected using explicit rules or principles. If associations between cues and optimal decisions can be learned implicitly, then implicit learning might contribute significantly to decision making under stress.

Implicitly acquired knowledge may be more useful than explicit knowledge to time-pressured decision making because it is more easily primed. This assessment is based on the transfer appropriate processing view of memory, according to which knowledge is retrieved best using the same cognitive processes that were used to learn it. Specifically, the cognitive processes used to retrieve time-pressured decisions and relevant knowledge might be similar to those used in implicit learning. The cognitive processes of implicit learning are hypothesized to result in the learning of covariations and other simple relations among physical stimulus features as a function of task performance (e.g., Bruner, 1992; Greenwald, 1992). Thus, a decision-making process that utilizes physical stimulus patterns, occurs in the course of task performance, and does not involve explicit recall seems especially compatible with
implicit learning and is likely to involve similar cognitive processes. Accordingly, implicitly acquired information may provide the basis for decisions made under pressure.

To examine the potential influence of implicit learning outside of the laboratory, where tasks and task environments can be very complex, this research extended previous investigations of implicit learning in relatively simple tasks by exploring implicit learning in a search task. Specifically, implicit learning of a 12-trial sequence in targets and keypress responses of a time-pressured search task was studied under single-task and dual-task workload conditions, as well as under different visual-attention demands. Workload and visual attention effects were examined because of their relevance to performance in operational environments. Multiple-task workloads are common in operational settings, as is the use of both distributed and focused visual attention strategies (e.g., by air traffic controllers when monitoring a large area of their display and when attending to the location of a specific aircraft, respectively). In the sections that follow, implicit learning will be defined and related to the concepts of explicit learning and implicit memory. The main paradigms used to study implicit learning will then be described, followed by a discussion of the possible loci of implicit learning benefits within perceptual-motor tasks. The final part of the introduction will be dedicated to the impact of workload and visual attention requirements on implicit learning.
Characteristics of Implicit Learning

Interest in implicit learning has been inspired partly by the goal of cognitive psychologists to identify cognitive systems and their neural substrates. A particularly important influence on the study of implicit learning has been progress toward this goal achieved by the study of implicit memory, which is memory that is demonstrated in the absence of intentional recall. Implicit memory was first demonstrated by amnesics who were unable to intentionally recall many events that continued to affect their performance (e.g., Warrington & Weiskrantz, 1970). This discovery held the promise that brain structures associated with conscious access to memories could be identified and additionally suggested that independent cognitive and neural systems may exist for intentional and unintentional memory recall (e.g., Squire & Zola-Morgan, 1991). Implicit memory subsequently has been demonstrated in normal subjects (e.g., Jacoby & Dallas, 1981), which meant that the study of implicit memory was no longer dependent on the availability of amnesic subjects, and consequently, it began to attract an enormous amount of interest. Progress in the study of implicit memory, in addition to Reber's (1967, 1989) introduction of implicit learning as a nonverbal, evolutionary ancestor to explicit learning (i.e., intentional learning) and Broadbent's (e.g., Berry & Broadbent, 1984; Broadbent, Fitzgerald, & Broadbent, 1986) finding of a dissociation between verbal and nonverbal measures of learning, encouraged the study of implicit learning as a means to identify brain structures associated with learning, and possibly to identify cognitive
and neural mechanisms for learning.

Implicit learning research initially characterized implicit learning as occurring without awareness (e.g., Hayes & Broadbent, 1988), nonverbalizable (e.g., Berry & Broadbent, 1984), and requiring few attentional resources (e.g., Cohen, Ivry, & Keele, 1990). These characteristics contrasted with those of explicit learning and indicated that implicit learning might depend on cognitive and neural systems that are independent of those used to learn explicitly (e.g., Hayes & Broadbent, 1988; Lewicki, Czyzewska, & Hoffman, 1987). However, a multiple-system view of implicit learning has more recently fallen out of favor, as will be discussed below. Currently, implicit learning is defined most often as learning without intention, a definition that does not preclude awareness, verbalizability, or attentional requirements (e.g., Stadler & Frensch, 1994).

For the purposes of the present research, implicit learning is defined as learning that occurs without intention. This definition is consistent with the definition of implicit learning given by Seger (1994, p. 164), according to which it is learning in the absence of hypothesis testing and is "an incidental consequence of the type and amount of cognitive processing performed." The definition also allows that implicit learning may be associated with an absence of awareness, nonverbalizability, and minimal attentional requirements, but is in no way contingent upon these qualities. These and other potential characteristics of implicit learning are discussed further below.
Can Learning With Awareness Be Implicit?

Some define implicit learning as learning without awareness (e.g., Hayes & Broadbent, 1988; Reber, 1989). However, given the difficulties in determining the role of awareness, a better definition seems to be learning without intention (e.g., Stadler & Frensch, 1994). This definition allows that learning can be implicit even when a person is aware of relationships, so long as learning is unintentional. This may occur when information is very complex or an explicit strategy requires too much attention. Nevertheless, the administration of tests of awareness (i.e., tests of explicit knowledge) is a common practice in studies of implicit learning because subjects are more likely to intentionally learn information of which they are aware. Hence, these tests serve as a means to identify the extent to which explicit learning may have contaminated implicit learning measures or, in other words, the extent to which learning may be implicit (e.g., Perruchet & Amorim, 1992; Willingham, Nissen, & Bullemer, 1989).

There has been a great deal of controversy over the comparison of explicit knowledge with implicit learning measures as a means to assess implicit learning. Specifically, deficiencies in measures of explicit knowledge relative to implicit learning measures might result from a failure to ask the right questions or to use sufficiently sensitive measures of explicit knowledge, rather than a lack of awareness (e.g., Perruchet & Amorim, 1992; Perruchet, Gallego, & Savy, 1990). In response to such criticisms, researchers have tried to develop more sensitive measures of awareness and frequently have
used multiple measures. Furthermore, a more flexible view of implicit learning has been adopted by many, according to which learning may be considered implicit even when subjects appear to be aware of the learned information. According to this view, implicit and explicit learning modes consist of a variety of learning modes that fall along a continuum, ranging from purely explicit to purely implicit learning modes (e.g., Berry, 1994; Berry & Dienes, 1991), or are characterized as sets of related learning processes. Learning processes from each set are used with particular types of stimuli and learning conditions, and may be used in combination with processes from the other set (e.g., Seger, 1994). Hence, instructions to learn will result in learning that tends to be intentional, or explicit, and an absence of instruction is supposed to result in learning that tends to be unintentional, or implicit.

This manner of operationalizing explicit and implicit learning avoids tests of awareness as indirect means to identify explicit learners. However, a more effective strategy might be to define learning as implicit or explicit at the individual subject level rather than in terms of a group tendency. To determine whether individual subjects used a mode of learning that was consistent with their instructional condition (i.e., instructed to learn or not instructed), learners could be asked if they tried to learn any stimulus or response patterns during task performance -- a technique that is consistent with the definition of implicit learning as learning without intention.
Attentional Requirements of Implicit Learning

The usefulness of implicit learning in complex task performance is partially dependent on its attentional requirements. That implicit learning should require few attentional resources is intuitively appealing. If you are not intending to learn something, why would you allocate significant attentional resources to learning it? Studies of the interference effects of irrelevant task information (e.g., studies that use the Stroop, Simon, and flanker task paradigms) suggest that the diversion of attentional resources away from the primary task to process irrelevant stimuli is not the source of interference. Rather, the interference seems to be caused by response competition between relevant and irrelevant stimuli (e.g., Cohen, Dunbar, & McClelland, 1990; MacLeod, 1991). This leaves open the possibility that processing irrelevant stimuli requires very few or no attentional resources.

Nevertheless, dual-task demands have been shown to impair implicit learning (e.g., Cohen et al., 1990; Curran & Keele, 1993; Frensch, Buchner, & Lin, 1994; Nissen & Bullemer, 1987; but see Stadler, 1995). This learning impairment does not seem to be caused by disruption of the primary task and indicates that attentional resources may play an important role in implicit learning. Additional evidence for this conclusion is disrupted implicit learning in Huntington's, Parkinson's, and Alzheimer's disease patients, possibly due to attentional deficits associated with these diseases (e.g., Ferraro, Balota, & Connor, 1993; Knopman & Nissen, 1991).

Many hypothesize that fewer attentional resources may be used
for the implicit learning of some types of relations than others. For example, Greenwald (1992) and Seger (1994) suggest that implicitly learning linear associations, relations used to make dynamic systems control decisions, and covariations among object features may utilize fewer attentional resources than implicitly learning hierarchical relationships, complex motoric patterns, and abstract covariations. Cohen et al. (1990) distinguish between single and hierarchical stimulus associations and have shown that the latter do not tend to be learned implicitly when attentional resources must be shared with a secondary tone-counting task.

Research by DeSchepper and Treisman (1996) indicates that implicit learning might occur in the absence of attention to the extent that it does not require memory retrieval. They found negative priming for novel items, even after a one-month delay, in a task that required same-different judgments of adjacent green and white items. An irrelevant red item that overlapped the green item on each trial was to be ignored. Negative priming was measured as the reaction time (RT) increase when a green (i.e., attended) item had been red in the preceding trial. Negative priming was thus evidence that unattended stimuli had been processed. DeSchepper and Treisman also found repetition priming for both attended and unattended novel items that increased across repetitions; however, the RT benefit was much smaller and more gradual for unattended items than for attended items. Hence, attended items were primed more than unattended items. In addition, attended items were primed approximately equally by unattended occurrences (i.e.,
negative priming) as by attended occurrences (i.e., repetition priming). DeSchepper and Treisman interpreted the latter finding to mean that attention was not needed to store stimulus occurrences. In contrast, the smaller priming effect for unattended items was seen as evidence that attention was required to retrieve past stimulus occurrences. Accordingly, implicit learning might be attention-free only if it does not involve retrieval processes. However, the use of implicitly acquired information to benefit performance most likely involves retrieval and therefore is likely to require attention.

Can Complex Relations Be Learned Implicitly?

The usefulness of implicit learning in complex task environments also depends on whether complex information and relationships can be learned implicitly. Bruner (1992) suggests that, in perception, whatever patterns and relationships are required to guide selective attention can be learned unconsciously (and therefore unintentionally). However, he agrees with Greenwald's (1992) assessment that these patterns and relationships are generally not complex and that the unconscious is "not very smart." In addition, Greenwald (1992) summarizes implicit learning research as mainly demonstrating the implicit learning of covariations or fragments of the complex rules used to generate experimental stimuli.

The question of what can be learned implicitly is far from resolved. Despite the pessimism of some, there are numerous examples of what seems to be implicit learning of complex information. Common examples of complex information that seems to be learned implicitly include rules of grammar, language, and
social interaction, as well as relations among the components of motoric skills. Implicit learning might also contribute to the performance of air traffic controllers, for example, who may implicitly learn efficient communication patterns, repetitive traffic patterns and activity, and cue patterns that are diagnostic of specific system malfunctions.

The Relationship of Implicit Learning to Explicit Learning

In contrast to implicit learning, explicit learning is intentional learning that includes hypothesis testing and instruction-based learning. Explicit learning utilizes attentional resources and learners typically are aware of and able to verbalize both explicit learning strategies and explicitly-acquired knowledge. Explicit learning is effective for learning rules, in contrast with implicit learning which may be more suited to learning instances (e.g., Shanks & St. John, 1994). Shanks and St. John (1994) have argued that explicit and implicit learning should be distinguished by whether learning is rule or instance-based, respectively. However, a variable that is easier to experimentally manipulate, like intention to learn, is viewed as a preferable means of distinguishing the two varieties of learning (e.g., Stadler & Frensch, 1994).

Based on their differences, particularly in terms of verbalizability, it has been hypothesized that explicit and implicit learning utilize different cognitive systems or mechanisms (e.g., Berry & Broadbent, 1988; Hayes and Broadbent, 1988). However, failures to experimentally dissociate explicit and implicit learning (e.g., Green & Shanks, 1993; Perruchet & Amorim, 1992), as well
as claims that implicit learning is actually explicit learning that is not detected by insensitive explicit learning measures (e.g., Perruchet & Amorim, 1992), have bolstered arguments against this multiple systems view. A single system view, according to which multiple modes of learning fall along a continuum between purely implicit and explicit learning, is currently favored (Berry, 1994; Berry & Dienes, 1991).

**The Relationship of Implicit Learning to Implicit Memory**

Implicit memory is memory for events and information that is not recalled intentionally. Operationally, it is the facilitation of task performance by previous experiences that are not consciously recalled (e.g., Roediger & McDermott, 1993; Schacter, 1987). Tests of implicit memory in normal subjects require subjects to perform a task that seems unrelated to an earlier study phase of the experiment. Implicit memory is measured as the extent to which performance on task items that were previously-studied (but are not recognized) is facilitated relative to performance on new items.

Berry and Dienes (1991) make the point that implicit learning and memory are logically dissociated. For example, a person can implicitly learn certain skills used in driving a car, such as effective mirror-use, and also have explicit memories of the episodes that contributed to that learning. In this case, the learning process may have been implicit and the skills implicitly acquired, but if the person is able to intentionally access memories of the learning episodes, then these memories would be explicit, rather than implicit. Implicit memory is demonstrated when knowledge has unintended effects on
performance, regardless of whether it was learned intentionally or unintentionally. In contrast, implicit learning requires only that learning processes, and not the retrieval of learned knowledge, be unintentional.

Despite their differences, independent research in these two areas has shown that implicit learning and implicit memory probably involve many of the same underlying processes. For example, they both might involve the unintentional retrieval of instances through activation by environmental and processing cues (e.g., Shanks & St. John, 1994). This mode of retrieval is associated with implicit memory (e.g., Roediger & Srinivas, 1993) and also has been associated with implicit learning of dynamic control systems (e.g., Dienes & Fahey, 1995), nonverbal category learning (e.g., Estes, 1986), time-pressured decision making (e.g., Hammond et al., 1987; Klein, 1993), and the automatization of search performance (e.g., Logan, 1988). Berry and Dienes (1991) describe additional similarities, including that both seem to be negatively affected by manipulations of stimulus surface features, unaffected by level of processing manipulations, independent of and more durable than explicit learning and memory, and demonstrated by amnesic patients. It should be noted that many of these qualities have not been carefully examined within the implicit learning literature and some are controversial within the implicit memory literature (e.g., durability). Thus, more research is needed to better understand the relationship between these two concepts.

Recent studies that contribute to understanding their relationship
used implicit memory paradigms to examine implicit memory phenomena that also might be considered learning phenomena. For example, performance facilitation for novel associations (Goshen-Gottstein & Moscovitch, 1995a, 1995b) and following multiple study trials (Challis & Sidhu, 1993; Logan, 1990) has been demonstrated using tests of implicit memory (e.g., lexical decision and general knowledge tests). These studies demonstrate that implicit memory paradigms may provide a means to evaluate implicit memory and learning in a similar context. To use them to examine implicit learning, it may only be necessary to alter study instructions so that learning instead of, or in addition to, the use of learned information is unintentional.

Implicit Learning Paradigms

Three paradigms are predominant in the study of implicit learning. These are the artificial grammar learning, control of dynamic systems, and sequence learning paradigms. Each paradigm emphasizes different cognitive processes and may involve different implicit learning processes (Seger, 1994). Consequently, each contributes to understanding different aspects of implicit learning.

The paradigms will be described below with respect to their main contributions to understanding implicit learning during complex task performance. Each paradigm provides a means to assess the benefits of implicit learning to particular skills that might be used in complex task performance. The artificial grammar learning paradigm can be used to assess the implicit learning of patterns in visual displays, the control of dynamic systems paradigm
can shed light on the contributions of implicit learning to decision making, and the sequence learning paradigm can be used to demonstrate the benefits of implicit learning to perceptual-motor performance. In addition, the paradigms have each been used to investigate whether complex and abstract information can be acquired implicitly or if implicit learning is limited to simple information about stimulus surface features.

Contributions of Artificial Grammar Learning Studies

The artificial grammar learning paradigm (e.g., Reber, 1967, 1989) requires that subjects try to memorize a set of consonant strings which, unbeknownst to the subjects, conforms to a set of rules. The test of implicit learning used in this paradigm is typically to categorize strings as grammatical or ungrammatical after being informed that the study strings adhered to a set of grammatical rules. Thus, this paradigm investigates the implicit learning of information processed for the purpose of memory storage, the learning of rule and pattern-based descriptions of that information, and the ability of subjects to explicitly use (i.e., make category judgments about) implicitly-acquired information. This paradigm contributes to understanding implicit learning in complex task environments by demonstrating if and how well abstract rules and complex relationships can be learned implicitly and applied.

The artificial grammar learning paradigm has been used primarily to address the question of whether abstract and generalizable information can be learned implicitly. This issue surfaced during the current century when Tolman (1949) introduced
field expectancies as a form of abstract learning in which
expectancies are learned from exposure to environmental
regularities. He argued that a rat tends to 'acquire an apprehension
not only of each group of immediate stimuli as it impinges on him
but also...for some of the interconnections or field relationships
between such groups of stimuli' (Tolman, 1949, p. 145). Current
research using the artificial grammar learning paradigm has
provided mixed support for abstract implicit learning. Evidence that
training with one letter set can transfer to another that follows the
same artificial grammar rules (e.g., Gomez & Schvaneveldt, 1994;
Mathews et al., 1989) and evidence that some grammar learning can
transfer across modalities (e.g., Altmann, Dienes, & Goode, 1995)
support the view that learning is abstract, although most do not go so
far as to argue that abstract rules are learned (but see Mathews,
1991). Instead, it is thought that abstract structural information may
be learned implicitly (e.g., Altmann et al., 1995; Brooks & Vokey,
1991; Dienes, Broadbent, & Berry, 1991; Dulany, Carlson, &
Dewey, 1984), and that most implicit grammar learning is restricted
to stimulus-specific information, and bigrams in particular (e.g.,
Shanks & St. John, 1994). Hence, these studies indicate that
implicitly learned information may be limited in its complexity.

Contributions of Control of Dynamic Systems Studies

The control of dynamic systems paradigm was introduced by
Broadbent (e.g., 1977) as a means to break away from serial models
of human information processing and to examine information
processing in terms of interactions among hierarchical levels of cognition. In studies that use this paradigm, participants' inputs partially determine the output values of a variable they are required to control. Output values may be determined by the output of the previous trial, the current input value, and random noise (e.g., Berry & Broadbent, 1984; Broadbent, 1977; Broadbent et al., 1986). Output values may also be determined by the current input value plus noise in salient rule conditions, or by the input value of the previous trial plus noise in nonsalient rule conditions (e.g., Berry & Broadbent, 1988). In most cases, the history of output values is displayed graphically during task performance. As one example, subjects are asked to control the output of a sugar production factory by manipulating the number of workers employed. Implicit learning has been demonstrated in the form of improved control task performance in the absence of a similar improvement in verbalizable system knowledge (e.g., Stanley, Mathews, Buss, & Kotler-Cope, 1989).

Research using the control of dynamic systems paradigm has demonstrated that implicit learning can occur in relatively complex decision-making environments. Studies that have used this paradigm have also demonstrated that implicit learning may be more suited than explicit learning to learning nonsalient rules within those environments (or to learning rules under conditions of increased task difficulty, given that task difficulty and rule salience were confounded [Berry, 1994]). Research using this paradigm also addresses the issue of whether implicit learning can be abstract.
Berry and Broadbent (1988) found that implicit learning did not tend to transfer across stimulus changes when the rules governing output were unchanged, suggesting that learning was tied to the surface features of the task. Similarly, Dienes and Fahey (1995) found that although a very salient and straightforward rule transferred to new system states, most learning was instance-based and did not transfer.

It is important to note that the effectiveness of the control of dynamic systems paradigm as a means of studying implicit learning may be questioned on two counts. First, participants are likely to realize that learning the rule for successfully regulating system outputs is the key to mastering the task. This may cause many participants to utilize an explicit learning strategy, such as hypothesis testing. Second, measures of explicit learning in this paradigm are mostly verbal reports, and verbal reports generally are not considered sensitive tools for assessing knowledge or cognitive processes such as learning. Their sensitivity depends on whether the right questions are asked by investigators and on whether knowledge is verbally represented, which is often not the case. According to Anderson's (1993) model of skill acquisition, ACT-R, knowledge becomes proceduralized with practice, with the result that verbalizable declarative knowledge may be lost. Furthermore, Nisbett and Wilson (1977) have shown that people are often unaware of the factors that influence their decisions.

Contributions of Sequence Learning Studies

A typical variation of the sequence learning paradigm uses a serial RT task in which stimuli are displayed in one of four
horizontally-aligned display positions and performers are required to press the response key assigned to the position of the stimulus (e.g., Nissen & Bullemer, 1987). Thus, the task objective is to press the key that corresponds spatially to the stimulus. Two conditions are usually performed, one in which stimulus positions and hence, responses, follow a repeating sequence and another in which they occur in a random order. Task performers are not told about the repeating sequence and often report no awareness of it. Implicit sequence learning has occurred if RTs are longer when positions are randomly-ordered than when they are sequenced (with the condition that the subject is not able to report the sequence).

The sequence learning paradigm has been used to examine the learning of perceptual and motoric regularities of which a performer is not aware. For example, it has been used to assess the complexity and structure of perceptual-motor patterns that can be learned implicitly, the role of attention in the implicit learning of perceptual-motor sequences, and whether sequence learning is primarily perceptual, motoric, or both. Implicit learning investigated using this paradigm may best approximate the form of implicit learning that occurs during the performance of tasks with dynamic perceptual and/or motor components, such as vehicle operation and air traffic control. Because of its relevance to operational perceptual-motor tasks like these, the sequence learning paradigm was used in the present research.

Like the artificial grammar learning paradigm, the sequence learning paradigm has been used to examine the potential for implicit
learning of abstract information. Unlike artificial grammar
learning, implicit sequence learning does not seem to transfer across
stimulus sets (e.g., Stadler, 1989; Willingham et al., 1989).
Cleeremans and McClelland (1990) suggest that implicit sequence
learning is tied to stimulus characteristics and, more specifically,
involves the acquisition of knowledge about sequence subsets of up
to three elements. In addition to this sequence knowledge and a
priming mechanism which Cleeremans and McClelland (1990)
theorize contributes to early stages of implicit learning, abstract (but
not generalizable) information about sequence structure seems to be
acquired (e.g., Stadler, 1992).

Summary of Results of Implicit Learning Studies

Research performed using the three above paradigms is
indicative of what can be expected of implicit learning during
operational and complex task performance. In general, it predicts
that implicit learning can benefit performance in these types of
circumstances, but that its role is limited. Implicit learning seems to
be limited to relatively simple relations that are largely
nongeneralizable. Research also suggests that implicit learning is
predominantly instance-based. That is, rules do not tend to be
learned implicitly and instead, learning may consist primarily of
instance storage. Implicit learning benefits may be demonstrated
when instances that contain predictive information about the present
trial and/or subsequent trials are retrieved in the course of task
performance through a cue activation process (i.e., a priming
process; e.g., Dienes & Fahey, 1995).
Despite its limits, implicit learning might be valuable in complex operational settings. However, research has focused on implicit learning in simplistic settings and generally has not extended into more realistic complex environments. It would not be difficult to achieve such an extension using the paradigms discussed above. For example, the implicit learning of patterns in display configurations could be examined using a version of the artificial grammar learning paradigm, implicit learning in more difficult and time-pressured decision-making tasks could be examined using the control of dynamic systems paradigm, and implicitly learning to anticipate stimulus and response information in more realistic task environments (e.g., with high perceptual and information processing demands) could be examined using the sequence learning paradigm.

Possible Loci of Implicit Learning

Identification of the locus or loci of implicit learning within the context of complex task performance has the potential of revealing in which task or variety of tasks implicit learning plays an important role. For example, if implicit learning is found to benefit perceptual operations, then the role of implicit learning in tasks with large perceptual components, such as air traffic control, should be studied and possibly expanded. Based on an information processing model of cognition, potential loci of implicit learning include perceptual, central (which include the mapping of stimuli to responses), and motoric processes. It should be noted that the majority of studies that have addressed the issue of where implicit learning occurs are sequence learning studies.
Perceptual Processes as a Possible Locus of Implicit Learning

Research suggests that the perceptual processing stage may be a locus of implicit learning. In particular, studies in which target locations follow a repeating sequence (e.g., the typical serial RT task used in sequence learning studies) suggest that attentional orienting to target locations represents a perceptual operation that can be implicitly learned (Nissen & Bullemer, 1990). Evidence for implicit learning of attentional orienting patterns comes from studies in which RTs were slowed by a change in the target digit location on every seventh trial from an outer corner to an inner corner of a quadrant of a search array (e.g., Lewicki et al., 1987; Stadler, 1989). Evidence that attentional orienting patterns may be learned implicitly is also provided by Mayr (1996), who found serial RT performance to be disrupted by the replacement of a stimulus location sequence with a randomized location order. In this study, stimulus identities were assigned to keypress responses, so learning the sequence in stimulus locations should have been limited to attentional orienting processes. Furthermore, Howard, Mutter, and Howard (1992) demonstrated implicit learning of a target location sequence in the absence of response executions. In their Experiment 1, subjects either responded in all trials of a serial RT task (the respond condition), or they responded only in those trials within each block that represented the first cycle of the target location sequence and observed the displays of all other trials (the observe condition). In Experiment 2, subjects in the observe condition observed all displays during the first three blocks of trials and responded in all trials of
the remaining five blocks. In both experiments, implicit learning in the observe condition was similar to that in the respond condition. Howard et al. concluded that implicit learning involves mainly perceptual processes.

In addition to attentional orienting, other perceptual operations that may benefit from implicit learning include search and encoding operations. Evidence for the implicit learning of search operations comes from Stadler (1989) and Treisman, Viera, and Hayes (1992). In Stadler's (1989) study, learning target locations could have involved either search or orienting operations, or both. In the study by Treisman et al., evidence was found for the implicit learning of contingencies between the features used to identify targets (color and orientation) and features that tended to co-occur with them. Implicit learning was evidenced by RT benefits associated with the co-occurrence of contingent features during performance of a conjunction search task (i.e., a search task in which targets are defined by a unique conjunction of features). Evidence for the implicit learning of encoding operations is provided by Fendrich, Healy, and Bourne (1991), who demonstrated entry time benefits for learned digit and motor sequences in a data entry task. An overall entry time advantage for old relative to new sequences was due to faster entry times for the first digit of each sequence. Fendrich et al. hypothesized that this initial keypress advantage reflected improved encoding and response preparation.
Central Processes as a Possible Locus of Implicit Learning

In many tasks, learning seems to occur in the response selection stage (e.g., Pashler & Baylis, 1991; Proctor & Dutta, 1994). Thus, this stage is also a probable locus of implicit learning. As evidence of this, Willingham, Nissen, and Bullemer (1989) showed that sequence learning did not occur when responses were not assigned to the sequenced stimulus feature (the stimulus was irrelevant to task performance, however) and was disrupted when S-R mappings were altered by switching to a different response feature (the motoric sequence was not altered). Willingham et al. concluded that series of stimulus-response (S-R) mappings were learned implicitly. In addition, implicit sequence learning is impaired by Huntington's and Parkinson's diseases, both of which are associated with motoric deficits that may disrupt the learning of S-R mappings (e.g., Ferraro et al., 1993; Knopman & Nissen, 1991).

Motoric Processes as a Possible Locus of Implicit Learning

Response execution, in contrast, does not appear to be a locus of implicit learning. Cohen, Ivry, and Keele (1990) came to this conclusion based on the absence of a performance disruption in their sequence learning study when the hand used to make responses was switched. Stadler (1989) similarly observed that implicit learning did not transfer to a new response apparatus that required the use of different fingers. Also, Fendrich, Healy, and Bourne (1991) found that response execution did not contribute to faster entry times in their study of perceptual and motoric sequence learning during performance of a digit entry task.
Conclusions About the Loci of Implicit Learning

The research summarized in this section is consistent with a response-selection locus of implicit learning. Although there might seem to be evidence for a perceptual locus as well, most of that evidence can be interpreted as support for a response-selection stage, instead. For example, the demonstration of sequence learning when responses are not executed (e.g., Howard et al., 1992) does not rule out the possibility that sequences of S-R mappings, rather than sequences of stimuli, were learned. Responses were not executed, but they might have been chosen. Likewise, an RT decrement caused by a change in stimulus patterns (e.g., Fendrich et al., 1991; Stadler, 1989) does not rule out the learning of S-R assignments because the assignments may have been disrupted by the stimulus change, as well.

Mayr (1996) realized the shortcomings of earlier studies that had tried to demonstrate implicit learning of perceptual operations. Consequently, his study, which demonstrated implicit learning of a stimulus-location sequence, was designed so that learning of the location sequence could be distinguished from learning associated with the selection of keypress responses. To rule out the possibility that sequence learning occurred because responses were chosen internally, responses were assigned to stimulus identities, which followed a sequence that was of a different length than the one followed by stimulus locations. In addition, unlike the stimulus color sequence that was not learned in Willingham et al. (1989), the stimulus location sequence used by Mayr was likely to be learned because location was relevant to task performance. In addition,
locations were far apart and focused attention was required to identify stimuli. Hence, learning the sequence could improve performance by reducing the time required to shift attention. Mayr's finding that the location sequence was implicitly learned may still be compatible with a response-selection locus of implicit learning, however, if shifting attention is considered to be a response to stimulus location.

According to an instance-based account of implicit learning with a response-selection locus, instances may contain the response selected, the stimulus information used to make the response decision, and the immediate consequences of the response. A change in either stimuli or responses could adversely affect instance retrieval, and thereby prevent access to information about immediate consequences. This would impair implicit sequence learning if access to instances that contain information about immediate consequences is responsible for implicit learning benefits. In the case of implicit sequence learning, the identities of the next stimulus and response might be the immediate consequences contained in instances. In the case of the control of dynamic systems paradigm, the system outputs that result from particular inputs might be the immediate consequences contained in instances.

An account of this nature is suggested by Zeißler (1994). Zeißler (1994) had subjects perform a focused-attention search task in which subjects were required to find a target letter and press the key assigned to its identity and found that the assignment of four target letters to a single response key, instead of to separate keys,
interfered with learning associations between responses and the location of the next stimulus. When four target letters were assigned to one response key and a fifth letter, V, was assigned to a second response key, response-relevant information was limited to whether or not the target letter was V. Consequently, neither relevant target information nor the response selection differed for the four targets that were not V, making it difficult to form separate instances that could be used to predict immediate consequences (i.e., the next stimulus location).

Implicit Learning During Complex Task Performance

Despite the complexity of many tasks in which implicit learning might be of value (e.g., air traffic control and systems troubleshooting), and the importance of assessing the role of implicit learning in such tasks, implicit learning has commonly been studied under conditions of relatively low complexity and workload. At most, subjects may be asked to perform a secondary tone-counting task with a serial RT task, which typically consists of just four stimuli mapped directly onto response keys. Even in studies that examined the implicit learning of rules predicting target locations in a 35-element search array (e.g., Lewicki et al., 1987; Stadler, 1989), rules were based on the sequence of target locations in six serial RT trials that preceded each search trial. A seemingly complex task was also used by Zießler (1994), but in the focused attention search task performed in his study of implicit learning, targets always appeared in a position that was adjacent to the target position of the preceding trial. Consequently, only a small portion of the search array and a
few stimuli were relevant in each trial.

The use of relatively simple tasks like these is surprising given the hypothesized capability of implicit learning mechanisms to process a great deal of complex information, and to do so more effectively than explicit learning mechanisms without utilizing significant attentional resources (e.g., Berry & Broadbent, 1988; Hayes & Broadbent, 1988; Lewicki et al., 1992; Seger, 1994). Furthermore, as noted in the introduction, implicit learning may be adapted to complex tasks through its resistance to stress and usefulness to time-pressured decision making. Research that is relevant to implicit learning in complex and operational tasks will be summarized in the following sections. This includes research of implicit learning during dual-task performance and under different visual attention demands. Although removed from operational environments, the findings of this research are predictive of the potential benefit of implicit learning to performance in a more complex setting.

The Effects of Multiple-Task Demands on Implicit Learning

Effects of Secondary Tasks on Implicit Learning

To test whether implicit learning requires significant attentional resources, a second task is commonly added to the implicit learning task. Such conditions also can provide insight into the usefulness of implicit learning in a multiple-task operational environment. As stated earlier, it is intuitively appealing that implicit learning should require few attentional resources. On this basis, implicit learning should be unaffected by the concurrent performance of multiple
tasks. Support for this assertion is provided by studies that have examined the related phenomenon of implicit memory and found secondary task performance at study to have no impact on implicit memory for studied items using perceptual tests of implicit memory (e.g., familiarity and lexical decision tests; Jacoby, Woloshyn, & Kelley, 1989; Parkin, Reid, & Russo, 1990; Squire & McKee, 1993).

Nevertheless, secondary random number generation tasks have been shown to have a negative impact on implicit learning in both artificial grammar (e.g., Dienes et al., 1991) and control of dynamic systems paradigms when the underlying rules are not salient (e.g., Green & Shanks, 1993). Significant decrements in sequence learning also have been found when subjects were required to perform a secondary tone-counting task (e.g., Cohen et al., 1990; Curran & Keele, 1993; Frensch et al, 1994; Nissen & Bullemer, 1987).

**Effects of Secondary Tasks on Attention**

Secondary tone-counting tasks are used frequently in the sequence-learning paradigm and seem to impact the learning of ambiguous associations (i.e., associations in which a particular sequence element is not followed by the same element each time it occurs; as in the sequence 124142) more than the learning of unique associations (i.e., associations in which a particular element is always followed by the same element, as in the sequence 124124). This has been interpreted as evidence for two dissociated learning mechanisms, one that utilizes attentional resources to form hierarchical relationships, and one that learns associative relationships without utilizing attentional resources (e.g., Cohen et
al., 1990; Curran & Keele, 1993).

To demonstrate that learning unique associations (implicitly or explicitly) does not require attention, Curran and Keele (1993) showed that the introduction of a secondary tone-counting task reduced, but did not completely abolish, the RT benefits associated with learning a hybrid sequence (i.e., a sequence with both unique and ambiguous associations of stimulus locations and responses). They claimed that RT benefits relative to initial performance (i.e., prior to obtaining practice) that still existed after the introduction of the secondary task represented benefits due to the learning of unique associations, which did not utilize attentional resources and therefore was not impaired when the secondary task was performed. Others, however, have argued that secondary tasks affect ambiguous more than unique-association learning not because different learning mechanisms with different attentional requirements are required, but because the associative mechanism that is used to learn both types of associations has more difficulty resolving ambiguous than unique associations, especially under dual-task conditions (Cleeremans & McClelland, 1991; Frensch et al., 1994; Stadler, 1992, 1995).

Frensch, Buchner, and Lin (1994) suggest that in the case of implicit sequence learning, this mechanism depends on the simultaneous availability of consecutive stimuli in short-term memory and that a secondary task reduces the resources available for storing these stimuli.
Interference by Secondary Tasks not Related to Attention

Stadler (1993, 1995) argued that because secondary tone-counting tasks require the performance of arithmetic operations at randomly-determined intervals (high and low tones are presented in a random order and high tones must be counted), they disrupt sequence learning by interfering with the sequence structure. He found that maintaining a memory load of letters (i.e., letter-set rehearsal) during serial RT performance disrupted sequence learning significantly less than tone counting (Stadler, 1995). Subjects in his study who were least aware of the sequence (as measured by a recognition test) and who were therefore supposedly relying most on an implicit (as opposed to an explicit) mode of learning, showed little or no disruption. Stadler's argument is further supported by the work of Schmidtke and Heuer (1996). Using a variation of the secondary tone-counting task in which a foot pedal was depressed in response to a high tone, they showed that the secondary task did not interfere with sequence learning if tones also followed a sequence, such that high tones occurred at predictable points in the location sequence. Disruption of either the tone sequence or of the location sequence disrupted performance of both tasks.

Another alternative to a purely attentional explanation of secondary task effects on implicit learning is derived from the instance-based account of implicit learning given in the summary of the preceding section. This account holds that implicit learning benefits are produced by the activation of a previously-stored instance which contains stimulus and response information for the
current event, and also information about the next event or other immediate consequences. Within this framework, a secondary task could disrupt implicit learning benefits by interfering with instance retrieval. For example, the attentional demands of a secondary task could prevent the retrieval of instances if, as DeSchepper and Treisman (1996) suggest, attention is required by retrieval processes. Furthermore, secondary task stimuli or responses could interfere with the retrieval of instances that are relevant to primary task performance. For example, in the case of secondary tone-counting tasks, the tones may interfere with the use of primary task perceptual cues to retrieve instances that are relevant to primary task performance. Implicit learning also might be impaired by secondary task information that is stored in instances along with primary task information. For example, implicit grammar learning might have been impaired by the storage of randomly-generated numbers along with the primary-task letter strings in Dienes et al. (1991).

The present research examines implicit learning during performance of a secondary letter-set rehearsal task and, according to both Stadler and the instance-based account of implicit learning, should not reveal any secondary task effects. Specifically, Stadler's (1995) explanation of secondary task effects predicts that implicit sequence learning will be unaffected by multiple task performance as long as none of the tasks disrupts the structure of the information to be learned. In addition, the instance-based account predicts that implicit learning will be affected only by secondary tasks that utilize all attentional resources, leaving none for instance retrieval, or by
secondary task perceptual information that interferes with the storage or retrieval of primary task information.

**Perceptual Demands and Their Effects on Implicit Learning**

If patterns in perceptual operations are implicitly learned or if implicit learning is instance-based, both the nature and amount of implicit learning that occurs might be affected by the perceptual attention and processing requirements of a given task. Two forms of perception that frequently are utilized in complex task environments are perception using a narrow spotlight of attention to examine a single stimulus and perception with a wider spotlight of attention to examine multiple stimuli in parallel.

**Varieties of Visual Attention**

Spotlight models of visual attention are based on resource theory, which conceptualizes attention as a limited resource. The smaller the spotlight, the more attentional resources seem to be allocated to processing stimuli within it (e.g., Eriksen & St. James, 1986; Eriksen & Yeh, 1985). Spotlight size can be manipulated by precuing a display area of a particular size, for example (e.g., Eriksen & St. James, 1986). Spotlight size is also affected by processing requirements. If stimuli cannot be distinguished when resources are distributed across a wide attentional spotlight, the spotlight can be narrowed so that stimuli will be processed further.

The use of wide and narrow spotlights of visual attention may also be characterized as the use of distributed and focused visual attention. When an attentional spotlight is used to process a single stimulus at a time, attention is focused. When a spotlight is used to
examine multiple stimuli simultaneously, attention is distributed across those stimuli. According to this view, the more stimuli within the spotlight, the more attention must be distributed.

Treisman's feature integration theory (FIT; e.g., Treisman, 1993; Treisman & Gelade, 1980) addresses which perceptual processes are performed and which perceptual information is processed when visual attention is distributed versus when it is focused. When visual attention is distributed across multiple stimuli, FIT proposes that simple features, or features for which there are specialized detector-neurons, such as color, illuminance, orientation, texture, and shape, are perceived. The parallel analysis of simple features includes the formation of feature maps, which consist of neural activation patterns that separately represent simple features across the visual field. When visual attention is focused on a single stimulus location, FIT proposes that simple features are conjoined. All feature map values that correspond to that location are processed and integrated to form a representation of the object in that location. Thus, focused visual attention is used to analyze individual stimuli in a serial manner and also plays an important role in the integration of perceptual information.

**Implicit Learning Under Distributed-Attention Conditions**

In general, the study of implicit learning under conditions of distributed visual attention has been neglected. In studies of implicit sequence learning, stimuli are usually presented one at a time and so distributed visual attention is rarely needed. In artificial grammar learning studies, focused attention is necessary to distinguish the
identities of letters in the study strings. Similarly, a focused
attention strategy is most likely adopted in the control of dynamic
systems paradigm when the displayed output of the preceding trial is
considered in order to choose the next input.

It is possible that the use of distributed visual attention in task
performance would interfere with implicit learning. For example,
patterns in target locations would not be learned if attention did not
move around a display, as when it is distributed. Implicit learning
also might not occur under distributed attention conditions if stimuli
are inadequately represented in memory with sparse detail. If, as
Frensch, Buchner, and Lin (1994) propose, stimulus relations are
learned implicitly while their representations are held in memory, an
absence of relevant information in these representations could hinder
learning. Alternatively, stimulus representations held in memory
might be sparse, but not inadequate, when stimuli are processed
using distributed attention. In this case, relevant information is more
likely to be learned implicitly because there is less irrelevant
information to be considered.

If implicit learning benefits are based on the retrieval of
instances that contain response and next-event information, then
implicit learning might be affected by visual attention only if there is
a change in the visual attention strategy (e.g., from distributed to
focused attention). Use of a new visual attention strategy might
cause a mismatch between perceived cues and stored stimulus
representations that were created using the old strategy. The
mismatch between old and new perceptual information could impair
instance retrieval and hence, disrupt implicit learning.

DeSchepper and Treisman (1996) addressed the representation of stimuli processed using focused, distributed, and no attention. Based on their finding of negative priming that was approximately equal to repetition priming, they argued that attention is not necessary to form a detailed representation of a novel shape in memory. However, their experiments included only two stimuli, one attended and one unattended, per trial. They hypothesize that when perceptual demands are high, as when many stimuli must be perceived simultaneously, unattended stimuli may be represented in the set of independent feature maps they activate (rather than as objects formed by feature map conjunctions) and stimuli perceived using distributed attention may be represented "as a single global object or texture and not as individuated elements (p. 42)."

Implicit learning under both focused and distributed visual attention conditions was examined by Treisman, Viera, and Hayes (1992). They looked at the implicit learning of contingencies between irrelevant and relevant target features during performance of a search task. Implicit learning of contingencies was found when targets were defined by a unique conjunction of predefined features (e.g., the conjunction of red and circular among distractors that were red and square and blue and circular). To discriminate targets defined by a unique feature conjunction, rather than by a single unique feature, focused attention is required (e.g., Treisman & Gelade, 1981). The contingencies were not learned, however, when subjects identified targets on the basis of a single, unique predefined
feature (e.g., a red target among green and blue distractors) that could be discriminated using distributed visual attention. Treisman et al. concluded that implicit contingency learning only occurs under conditions of focused visual attention.

Nevertheless, their results do not rule out the possibility of implicit learning under conditions of distributed visual attention. Feature contingencies and sequences might still be learned implicitly when distributed visual attention is used if all contingent or sequenced features are relevant to stated task objectives. Alternatively, contingencies between features belonging to a particular stimulus (e.g., between the color and shape of a target stimulus) may not be learned unless they are integrated using focused attention. If so, it still should be possible to learn feature contingencies and patterns implicitly under conditions of distributed attention if they can be perceived without integrating features (as in the case of contingencies between colors of different stimuli).

Implicit learning of contingencies under conditions of distributed visual attention was demonstrated by Miller (1987) in a study that found target letter identification RT to be affected by contingencies between target and flanker letter identities. The effect of target-flanker compatibility on target identification has been characterized as a failure of selective attention (e.g., Paquet & Lortie, 1990; Yantis & Johnston, 1990), although it might be better characterized as a failure of early selective attention. Evidence of a flanker compatibility effect, albeit of reduced size, when flankers are separated by as much as 4.6 deg from the target (Miller, 1991), and
under a variety of other conditions intended to facilitate selective attention (e.g., Miller, 1991, 1987; Paquet & Lortie, 1990; Yantis & Johnston, 1990), suggests that flankers are processed during an early distributed analysis of the visual field, prior to focused-attention processing of the target. Miller's (1987) finding that RT is affected by target-flanker contingencies suggests that implicit learning is possible when stimuli are perceived using distributed attention.

**Interactive Effects of Visual Attention and Mental Workload on Implicit Learning**

Mental workload might contribute to the effects of visual attention requirements on implicit learning. A high workload might interfere with learning more when focused attention is used than when distributed attention is used because focused attention requires more attentional resources. Workload may also affect a subject's perceptual processing strategy. Increases in visual load have been shown to induce a focused-attention strategy (e.g., Lavie, 1995; Yantis & Johnston, 1990; Williams, 1988). Hence, a high workload might result in the use of focused attention in conditions that are typically conducive to distributed attentional processing. Accordingly, task performance and implicit learning benefits under distributed attention might be reduced when a high workload is imposed. Conversely, a high workload might render learning under focused-attention conditions more similar to learning under distributed-attention conditions if it reduces the ability to focus attention, as suggested by Ste-Marie and Jacoby (1993). According to this hypothesis, task performance and implicit learning benefits
from the use of focused attention should be affected by a high workload. The conflicting data and hypotheses suggest that there is still much to learn about the interaction of workload and perception.

**Overview of Present Experiments**

This research investigated the hypothesis that implicit learning can benefit performance in complex task environments. The sequence learning paradigm was used to study implicit learning, however, instead of a serial RT task, subjects performed a search task. In contrast to the single-step requirement of feature identification in the serial RT task, a search task requires the additional step of finding a target among distractor stimuli. Thus, it features a higher perceptual load and a somewhat more complex procedure than a serial RT task.

In Experiment 1, the effects of workload and perceptual requirements were examined. A time-pressured search task was performed with and without a secondary letter-set rehearsal task. Letter-set rehearsal was chosen as a secondary task, instead of the commonly-used tone-counting task, because it should not disrupt the structure of the sequence. The task either required the allocation of focused visual attention to the target or could be performed using a distributed visual attention strategy. The response-relevant feature, target orientation, followed a 12-trial sequence that included both unique and ambiguous associations (i.e., it was a hybrid sequence). Sequence learning was assessed by examining changes in performance when, after many blocks of search task performance, target orientations switched from the predetermined sequence to a
randomized order.

Experiment 2 attempted to demonstrate implicit learning of perceptual information in the absence of sequenced responses. As noted earlier, most findings of implicit learning of perceptual operations can alternatively be explained as learning of S-R mapping rules. In this experiment, the feature used to find the target (color) followed a 12-trial sequence. Once the target was found, responses were made by identifying a second target feature (location) and pressing the corresponding key. Hence, the S-R mapping did not follow the target-feature sequence and evidence of sequence learning would support a perceptual-encoding locus of implicit learning.

As in Experiment 1, the search task was performed under perceptual requirements intended to cause the allocation of either focused or distributed visual attention to the target. Implicit learning of the target-feature sequence under either of the conditions in this experiment would provide evidence that sequential patterns in perceptual encoding operations can be implicitly learned. Conversely, a finding that sequence learning only occurred in a control condition in which the response feature, target location, also followed the same 12-trial sequence, would be strong evidence against implicit learning of sequential patterns in perceptual information.

In interpreting the results of implicit sequence learning studies, subjects' use of explicit learning modes is a recurring problem. Seger (1994) has described implicit learning as suited to learning relationships that are difficult to learn explicitly, such as those that
are complex, not easily parsed, or not salient. Hence, the sequences that typically are used may consist of associations that are simple and straightforward, and therefore more compatible with explicit than implicit learning. Pilot experiments revealed that in the context of search task performance, subjects were not likely to notice or explicitly learn sequence-related regularities when target orientations followed a 12-trial hybrid sequence. Neither implicit nor explicit learning seemed to occur when the sequence was longer and more complex (i.e., 20 trials long and with only ambiguous associations).

To gauge the extent to which the 12-trial hybrid sequence was explicitly learned in the present research and to identify explicit learners, participants were asked if they had noticed any stimulus patterns and, if so, if they had tried to learn them. Participants who answered the latter question positively were considered explicit learners, contingent upon high sequence generation or recognition test scores. Generation and recognition tests like those recommended by Perruchet and Amorim (1992) were administered to assess explicit sequence knowledge. High scores on these tests would indicate that a subject's report of trying to learn a stimulus or response pattern was a valid indicator of explicit sequence learning (i.e., the subject had not tried to learn a nonexistent pattern).

Experiment 1

In the first experiment, implicit learning during performance of a time-pressured search task was examined. A 12-trial sequence was followed by the response feature, target orientation, and hence, by responses. The search arrays in Experiments 1a and 1b consisted of
12 or 16 filled rectangular bars that varied in color and orientation, with four possible values of each feature. Search arrays in Experiment 1c were 6 or 9 capital letters that varied in orientation and identity, with four possible values of each. In Experiment 1d, stimuli were bars used in the search tasks of Experiments 1a and 1b, presented one at a time in a serial RT task. Responses were made to target orientations in each case.

In Experiment 1a, perceptual requirements and mental workload were manipulated. Half of the participants were required to locate a subgroup of 4 or 8 adjacent bars of the same color and identify the unique orientation assigned to the one that differed in orientation from other bars in the subgroup (all bars in the subgroup except the target had the same orientation). According to FIT (e.g., Treisman & Gelade, 1981; Treisman & Gormican, 1988), the unique target orientation within the spotlight of attention distributed across the subgroup of same-color bars should "pop-out" of the display.

The other half of the participants were required to locate a single bar (the target) based on its unique color and identify its orientation. This is similar to the procedure used by Luck, Fan, and Hillyard (1993). In their study of the brain activity associated with focused attention, subjects located a distinctively-colored element in a search array and identified its shape. FIT predicts that target features are conjoined when given focused attention. In addition, resource theories of visual attention predict that a stimulus is processed more thoroughly when attention is focused on it alone, as in this case, than when it is distributed over a subgroup of items (e.g., Duncan, 1985;
Eriksen & Yeh, 1985).

Workload was manipulated by requiring half of the subjects in each perceptual requirement condition to perform a secondary letter-set rehearsal task. The effects of secondary memory load tasks have been shown to be additive with factors including stimulus array size, stimulus discriminability, and S-R compatibility (Logan, 1979). In addition, this task should not disrupt the sequence structure (e.g., Stadler, 1995).

In Experiment 1b, participants were informed of the 12-trial sequence and were instructed to try to learn it (i.e., to use an explicit learning mode) during search task performance. The search task was the same as the one in Experiment 1a that was to be performed using distributed visual attention. Half of the subjects performed a secondary letter-set rehearsal task. Explicit sequence learning under different workload conditions was contrasted with sequence learning in Experiment 1a, which was implicit.

In Experiment 1c, participants were required to locate a unique letter in each search array and identify its orientation. According to FIT, because the letters could not be distinguished by their simple features (they were all composed of white horizontal and vertical lines of similar lengths), a feature conjunction search process was required to serially process search elements using focused attention (e.g., Treisman & Gelade, 1981; Treisman & Sato, 1990). This use of focused attention to process and conjoin multiple stimulus features contrasts with Experiment 1a, in which attention was assumed to be focused because it had been cued to the location of a single stimulus.
In Experiment 1d, implicit learning of the 12-trial sequence of target orientations was examined in the context of serial RT task performance. This provided a baseline of implicit learning with which implicit learning in the more complex search task could be compared.

**Experiment 1a**

This experiment was expected to demonstrate implicit sequence learning during performance of a relatively complex search task. It additionally examined the effects of workload and different perceptual requirements. Sequence learning should be unaffected by workload differences if it requires only minimal attentional resources. However, perceptual requirements might affect the representation of stimuli in memory and thereby affect factors that may contribute to implicit sequence learning, such as the number of stimulus representations that can be held in short term memory at one time, the amount of irrelevant perceptual information represented, how well relevant perceptual information is represented, and the effectiveness of retrieval cues.

**Method**

**Facilities.** The experiment was performed in a Lackland AFB facility with sixteen 80-586 MHz, twenty-four 80-486 MHz, and thirty-eight 80-386 MHz DOS-based computers with video graphics adaptor (VGA) color monitors. Each computer was surrounded on three sides by partitions. The experiment was programmed using the Micro Experimental Laboratory (MEL) software package (Schneider, 1988).
**Participants and Design.** The participants were 152 male and 34 female volunteers from the United States Air Force (USAF) basic training program at Lackland Air Force Base (LAFB), who had approximately 20/20 or corrected-to-normal vision. Seven subjects reported color deficiencies in vision or made at least four color identification errors on a color test. Twenty-three reported a left-hand preference for throwing or writing. Forty-two reported left-eye dominance.

Participants were each randomly assigned to one of four groups created by the factorial combination of perceptual requirement (wide or narrow-focus) and workload (single or dual-task). Within-subject factors were set size (12 vs. 16 bars in narrow-focus search arrays and 4 vs. 8 bars in the same-color subgroups of wide-focus arrays) and block (nine blocks of 120 trials). The experiment began at approximately 0730 hrs and lasted approximately 1.5 hrs. Participants were initially told that the experiment was designed to study visual perception. They were debriefed on its use to study learning upon completing the experiment.

**Search array.** Stimuli were red, yellow, green, or blue, 0.3 x 1.2 cm bars oriented 15 deg left, 15 deg right, 75 deg left, or 75 deg right, and presented on a black background. They were displayed in a centered 4 element x 4 element array surrounded by an 8 x 8 cm box drawn with a 2-mm white line. Head position was not fixed. However, based on a viewing distance of 55 cm, the search array and surrounding box subtended a visual angle of 8.3 deg horizontally and vertically.
In **narrow-focus** conditions, stimuli appeared in 12 or 16 of the 16 possible array positions (see Figure 1). In the 12-stimulus displays, stimuli appeared in three randomly-determined adjacent rows or columns. Set size in each trial was randomly determined with the constraint that each size was used equally often.

![Figure 1](image)

**Figure 1.** A display like those in the narrow-focus condition of Experiment 1a. The task was to find the uniquely-colored target bar and identify its orientation. The target is in the lower left corner and the correct response is 15 deg left. **Note.** Different shades represent different colors.

In **wide-focus** conditions, stimuli appeared in all 16 array positions (see Figure 2). A rectangular outline surrounded each of two four-element quadrants in the array and a third rectangle surrounded the remaining eight elements (two quadrants). The
division of the four quadrants into three groups was randomly determined in each trial. The rectangular outline in which the target bar appeared, the target rectangle, was the color of the target. The remaining two non-target rectangles were grey.

Figure 2. A display like those in the wide-focus condition of Experiment 1a. The task was to find the group of same-color bars and identify the orientation of the uniquely-oriented bar. The target is in the lower left corner and the correct response is 15 deg left. Note. Different shades represent different colors.

Targets. The first five and last two blocks of trials were sequenced-orientation blocks, in which target orientation followed the 12-trial sequence 3-4-1-2-4-1-2-3-4-1-3-2, where the numbers 1, 2, 3, and 4 represent the orientations 75 deg left, 15 deg left, 15 deg right, and 75 deg right and also keypresses made with the index,
middle, ring, and little fingers, respectively. Each element occurred equally often in this sequence which contained unique (e.g., 4 always precedes 1) and ambiguous (e.g., 1 precedes 2 as well as 3) associations, and redundancies (e.g., 2-3-4-1 occurs twice). Blocks 6 and 7 were randomized-orientation blocks, in which orientation was randomly assigned to targets with the constraint that it was not the same in consecutive trials.

Target color and location were assigned randomly without consecutive repetition in the wide-focus condition. In the narrow-focus condition, location was assigned randomly, but color followed the 12-trial sequence 3-1-2-4-1-2-3-1-4-3-2-1 where the elements 1, 2, 3, and 4 represented the colors red, blue, green, and yellow, respectively.

**Distractors.** In the narrow-focus condition, two of the three colors not assigned to the target were assigned to randomly-chosen sets of approximately equal numbers of distractors (e.g., sets of five and six distractors when the display set size was twelve). In addition, different orientations were assigned to four randomly-chosen sets of approximately equal numbers of distractors.

In the wide-focus condition, orientations not assigned to the target were assigned to randomly-chosen sets of distractors with the constraints that if the target bar was oriented 15 deg left or right, the distractors assigned to the target rectangle were oriented 75 deg left or right and vice versa and that distractors assigned to each nontarget rectangles had the same orientation with one exception. Distractors in the target rectangle were the same color as the target. Nontarget
colors were each randomly assigned to pairs of distractors within nontarget, single-quadrant rectangles and to the two pairs and set of four distractors within nontarget, double-quadrant rectangles.

Procedure. Each trial began with the outline of a box displayed centrally for 0.5 s, followed by the appearance of a search array within it. Display time was 2 s in the first block of 120 trials, 1.75 s in the second, and 1.5 s in the remainder. Responses made up to 0.5 s after display termination were accepted. A 50-ms high-pitched tone occurred when an error was made. The index, middle, ring, and little fingers of the right hand were used to make responses using four adjacent keys on the lowest row of the keyboard. Target bar orientations 75 deg left, 15 deg left, 15 deg right, and 75 deg right were assigned from left to right to response keys.

In narrow-focus conditions, participants searched arrays of 12 or 16 bars for the uniquely-colored bar (the target) and pressed the key assigned to its orientation. In wide-focus conditions, participants searched arrays of 16 bars for a subgroup of 4 or 8 same-color bars (surrounded by a rectangle of the same color) and pressed the key assigned to the orientation of the uniquely-oriented bar (the target) within that subgroup.

In dual-task conditions, a letter set of five consonants, randomly-chosen without replacement, was displayed in the center of the display for 8 s prior to each block of trials for the first 71 participants. For the remaining 24 participants, a new letter set was displayed for 5 s prior to and also in the middle of each block.\(^1\)

\(^1\) This change in methods was made without examining the partially-collected data
Participants were instructed to repeat the letters to themselves during search task performance. Before each new letter set was displayed, they recalled the last set by typing the letters in order. The correct set was displayed after each recall test.

Mean RT and percent error (PE) were displayed as feedback after each block of trials. Enforced 30-s and 15-s breaks separated blocks in single-task and dual-task conditions, respectively, and longer breaks were encouraged. Enforced break times differed because letter-set recall and study periods lengthened breaks in dual-task conditions.

Nine blocks of 120 trials were performed after 100 practice trials. In sequenced-orientation blocks (i.e., Blocks 1 - 5, 8, and 9), the response dimension, target orientation, followed a repeating 12-trial sequence. Each of these blocks began at a different point in the sequence.

After the nine blocks of search task trials, participants were asked if they had noticed any patterns in target color or orientation and, if so, to describe them and indicate whether they had tried to learn them. They were then informed of the repeating sequence in target orientations and were asked to try to generate the sequence using the response keys (i.e., to perform the sequence generation test). Participants in dual-task conditions also reported whether they had rehearsed the letter sets as instructed.

---

and is a consequence of concern over whether the first version of the secondary task was demanding enough. Differences between performance with each of the secondary task versions were minimal and will be described in the results section. Performance criteria for inclusion in data analyses were met by 35 and 19 of the subjects who performed the first and second versions, respectively.
The sequence recognition test was performed next. In each of 36 trials, participants performed four search-task trials and then rated the familiarity of the sub-sequence of target orientations on a 4-point scale labeled as follows: (1) the sub-sequence followed the predetermined sequence, (2) the sub-sequence seemed familiar, (3) the sub-sequence seemed unfamiliar, and (4) the sub-sequence did not follow the predetermined sequence. One-third of the trials were comprised of the 12 four-trial sub-sequences derived from the sequence, one-third were comprised of new sub-sequences with structural constraints similar to those of the sequence, and one-third were comprised of new sub-sequences with fewer structural constraints (e.g., they included consecutive repetitions). The three types of trials were intermixed and displayed in a different random order for each subject.

The last 29 participants in dual-task conditions took a test of working memory after the recognition test. Seven consonant strings, each composed by random sampling without replacement, increased from three to nine elements across each of two sets of seven trials. In each trial, a string appeared from 3.9 to 5.7 s (each additional element increased display time by 0.3 s) followed by a delay of 2.5 s, then a prompt to recall the string. Subjects were instructed to type each string of letters in the correct order and then to press the enter key.

Finally, subjects performed a color test. In each of 16 trials, a 2.7 x 1.3 cm, colored bar was centrally displayed above a list of eight numbered color names (brown, pink, grey, yellow, blue,
green, purple, and red). Subjects pressed a numeric key to indicate which color name matched the color of the bar.

Results and Discussion

The data of 29 participants were lost due to computer program malfunctions. Of the remaining 157 participants, 122 met the accuracy criterion of 75% or better. Seven of these subjects were excluded from analyses because of low secondary task scores. In addition, subjects who appeared to engage in explicit learning (i.e., who reported trying to learn a pattern they had noticed and who also had high generation or recognition test scores; \( n = 14 \)) were excluded from analyses except when explicitly stated otherwise.

Statistical comparisons of the performance of subjects who had color-deficient vision (\( n = 9 \)), or who were left-handed (\( n = 19 \)) or left-eye dominant (\( n = 29 \)) with the performance of the other subjects revealed no differences. Nor did the performance of males (\( n = 95 \)) and females (\( n = 20 \)) differ. Hence, their data were submitted together to the analyses described below. In addition, the second version of the secondary task (\( n = 19 \)) did not affect search task performance or sequence learning more than the first version (\( n = 35 \)), compared to single-task performance, despite the decreased study time and increased number of strings.\(^2\)

For the 115 participants included in the analyses below, trials

---

\(^2\) An interaction of secondary task version with workload for search task RT (F(1,111)=5.70, p<.02, MSE = 39,068) was caused by a larger RT difference between single and dual-task conditions when the first version (\( M = 69.5 \) ms) than when the second version (\( M = -9.95 \) ms) was performed. It is important to note that sequence learning did not seem to be affected by secondary task version.
were discarded if the RT was less than 150 ms or if a response was not made before the response period expired (1.9% of trials), and incorrect trials were excluded from RT analyses (mean PE = 6.1%).

**Sequence Learning.** Sequence learning was quantified by the differences in mean RT and PE between Blocks 5 and 6, caused by the replacement of the target orientation sequence with a randomized order. These differences are shown in the first column of Tables 1 and 2, respectively. In addition, Figure 3 shows mean RTs across all nine blocks of trials and the RT disruption between Blocks 5 and 6 in the four implicit learning conditions.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Sequence Associations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
</tr>
<tr>
<td>Narrow-Focus/Single-Task</td>
<td>30.78</td>
</tr>
<tr>
<td>n = 30</td>
<td>(41.51)</td>
</tr>
<tr>
<td>Narrow-Focus/Dual-Task</td>
<td>31.92</td>
</tr>
<tr>
<td>n = 28</td>
<td>(52.91)</td>
</tr>
<tr>
<td>Wide-Focus/Single-Task</td>
<td>20.74</td>
</tr>
<tr>
<td>n = 31</td>
<td>(50.77)</td>
</tr>
<tr>
<td>Wide-Focus/Dual-Task</td>
<td>23.05</td>
</tr>
<tr>
<td>n = 26</td>
<td>(55.96)</td>
</tr>
</tbody>
</table>

*Note.* Standard deviations of reaction time increases are in parentheses.
Table 2
Mean Increases in Percent Errors from Block 5 to Block 6 for Different Types of Sequence Associations in Experiment 1a

<table>
<thead>
<tr>
<th>Condition</th>
<th>Sequence Associations</th>
<th>All</th>
<th>Unique</th>
<th>Ambiguous</th>
</tr>
</thead>
<tbody>
<tr>
<td>Narrow-Focus/Single-Task</td>
<td>1.1</td>
<td>1.7</td>
<td>1.1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.3)</td>
<td>(3.8)</td>
<td>(4.2)</td>
<td></td>
</tr>
<tr>
<td>Narrow-Focus/Dual-Task</td>
<td>0.8</td>
<td>1.6</td>
<td>0.5</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.5)</td>
<td>(3.2)</td>
<td>(3.2)</td>
<td></td>
</tr>
<tr>
<td>Wide-Focus/Single-Task</td>
<td>0.7</td>
<td>0.7</td>
<td>0.7</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.1)</td>
<td>(6.0)</td>
<td>(5.2)</td>
<td></td>
</tr>
<tr>
<td>Wide-Focus/Dual-Task</td>
<td>1.7</td>
<td>0.8</td>
<td>2.0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.3)</td>
<td>(9.4)</td>
<td>(6.6)</td>
<td></td>
</tr>
</tbody>
</table>

Note. Standard deviations of percent error increases are in parentheses.

Separate ANOVAs with block (Block 5 vs. 6), workload (single vs. dual-task), and perceptual requirement (wide vs. narrow-focus) as factors were used to assess RT and PE differences between Blocks 5 and 6. Results are given in Appendix A. To summarize, main effects of block and perceptual requirement on RTs and PEs were found, in addition to a marginally significant effect of workload on RTs only. Implicit sequence learning was demonstrated by an increase in RTs ($F(1,111) = 32.03$, $p = .0001$, $MSE = 1,267$) and in PEs ($F(1,111) = 7.36$, $p = .008$, $MSE = 0.0009$) between Blocks 5 and 6. Examination of individual subject RTs revealed evidence of implicit sequence learning by 74% of subjects (83% in the narrow-focus condition and 65% in the wide-focus condition). The main
effect of perceptual requirement on RTs ($F(1,111) = 89.84, p = .0001, \text{MSE} = 22,617$) and PEs ($F(1,111) = 36.45, p = .0001, \text{MSE} = 0.005$) indicated that search task performance was better under narrow-focus than wide-focus conditions. The marginally significant effect of workload on RTs ($F(1,111)=2.78, p =.098, \text{MSE} = 22,617$) probably reflects an effect of workload that primarily occurred in the wide-focus condition, as can be seen in Figure 3. A statistical test of workload was significant in that condition ($F(1,55) = 4.22, p = .045, \text{MSE} = 26,928$), but not in the narrow-focus condition.

These analyses demonstrate implicit sequence learning that is unaffected by perceptual requirements or workload. In contrast, search-task performance during Blocks 5 and 6 was better under narrow-focus conditions and was affected by workload in wide-focus conditions.

**Unique and Ambiguous-Association Learning.** In sequenced-orientation blocks, the target orientation 75 deg left always followed the target orientation 75 deg right. Thus, the two were uniquely-associated. Implicit learning of unique associations has been shown to be relatively immune to the effects of secondary tasks (e.g., Cohen et al., 1990; Curran & Keele, 1992). As expected, this was also the case in the present experiment.
Figure 3. Mean reaction time (in ms) as a function of block under different perceptual requirement and workload conditions in Experiment 1a.
The results of ANOVAs performed on RTs and PEs for the uniquely-predicted target orientation were similar to the results of the overall sequence learning analysis described above, although in these analyses, the interaction of workload with perceptual requirement was marginally significant ($p = .091$). The complete set of results is given in Appendix B. In addition, mean RT and PE differences between Blocks 5 and 6 for the uniquely-predicted target orientation are shown in the second column of Tables 1 and 2.

All other associations between target orientations were ambiguous. In contrast with implicit learning of unique associations, implicit learning of ambiguous associations has been shown to be adversely affected by a secondary tone-counting task (e.g., Cohen et al., 1990; Nissen & Bullemer, 1987). The results of the present experiment conflict with this finding, as no effect of workload was found, perhaps because a different secondary task (i.e., letter-set rehearsal) was used. The results of ANOVAs performed on RTs and PEs of ambiguously-associated target orientations paralleled those of the overall sequence learning analysis in all other respects, too. The complete results are given in Appendix C. In addition, mean RT and PE differences between Blocks 5 and 6 for ambiguously-associated target orientations are shown in the third column of Tables 1 and 2.

The Effects of Search Task Accuracy on Sequence Learning. With greater task complexity, the opportunity for error increases. If sequence learning involves learning series of S-R mappings or of response operations, then a high error rate might be responsible for impaired implicit sequence learning during complex task
performance. Therefore, subjects in each perceptual requirement condition were divided into two groups according to their accuracy rates, and implicit learning by each accuracy group was assessed.

Table 3
Mean Increases in Reaction Time (in ms) and Percent Errors Between Blocks 5 and 6 for Groups of High-Accuracy and Low-Accuracy Subjects in Experiment 1a

<table>
<thead>
<tr>
<th>Condition</th>
<th>RT</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Accuracy</td>
<td>Group</td>
</tr>
<tr>
<td></td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Narrow-Focus/Single-Task</td>
<td>29.12</td>
<td>32.94</td>
</tr>
<tr>
<td></td>
<td>(45.78)</td>
<td>(36.88)</td>
</tr>
<tr>
<td>Narrow-Focus/Dual-Task</td>
<td>35.40</td>
<td>27.91</td>
</tr>
<tr>
<td></td>
<td>(28.81)</td>
<td>(72.79)</td>
</tr>
<tr>
<td>Wide-Focus/Single-Task</td>
<td>27.19</td>
<td>13.86</td>
</tr>
<tr>
<td></td>
<td>(41.19)</td>
<td>(60.06)</td>
</tr>
<tr>
<td>Wide-Focus/Dual-Task</td>
<td>30.78</td>
<td>16.43</td>
</tr>
<tr>
<td></td>
<td>(50.82)</td>
<td>(61.10)</td>
</tr>
</tbody>
</table>

Note. Standard deviations of increases in reaction time and percent errors are in parentheses. Negative numbers indicate performance improvement, rather than disruption.

In the narrow-focus condition, subjects were assigned to the high accuracy group if their accuracy rate was 96% or better (M = 0.977, SD = 0.017, n = 32) and to the low accuracy group if their accuracy rate was between 75 and 96% (M = 0.919, SD = 0.079, n = 26). In the wide-focus condition, subjects were assigned to the high accuracy group if their accuracy rate was 91% or better (M = 0.939, SD =
0.032, \( n = 28 \)) and to the low accuracy group if their accuracy rate was between 75 and 91\% (\( M = 0.850, SD = 0.090, n = 29 \)). Mean RT and PE changes between Blocks 5 and 6 for each group and each between-subjects condition are shown in Table 3.

The importance of overall accuracy to learning was assessed by performing separate ANOVAs of the narrow-focus and wide-focus data with accuracy group (low vs. high), block (Block 5 vs. 6), and workload (single vs. dual-task) as factors. These analyses yielded results similar to those reported for block and workload in the preceding section. In addition, the difference between high and low accuracy groups was significant (\( p = .0001 \)). There was also a main effect of accuracy group on RTs in the narrow-focus condition only (\( F(1,54) = 8.7, p = .005, MSE = 16,390 \)) and an interaction of block and accuracy group for PEs in the narrow-focus condition (\( F(1,54) = 6.3, p = .015, MSE = 0.0004 \)), which, contrary to expectations, indicated that there was a larger effect of block (i.e., more evidence of sequence learning) in the low accuracy group than in the high accuracy group. ANOVAs performed to assess simple main effects revealed an effect of block in the low accuracy group (\( F(1,24) = 9.46, p = .005, MSE = 0.0005 \)), but not in the high accuracy group of the narrow-focus condition. These analyses of block within each accuracy group also revealed an RT difference between blocks for each accuracy group under both wide-focus and narrow-focus conditions (all \( p \)'s < .015), with the exception of the low-accuracy group of the wide-focus condition. A marginally significant Workload x Accuracy Group interaction for PEs in both narrow-
focus and wide-focus conditions ($E(1,54) = 3.68$, $p = .06$, $\text{MSE} = 0.0016$ and $E(1,53) = 3.04$, $p = .087$, $\text{MSE} = 0.003$, respectively) also was unexpected. It reflected smaller differences between the PE rates of high and low accuracy groups under dual-task conditions, compared to single-task conditions, seemingly because the low accuracy groups tended to be less accurate in single-task than in dual-task conditions.

These analyses suggest that overall accuracy affects implicit sequence learning. In particular, subjects in the group with the lowest accuracy rate (i.e., the low-accuracy group in the wide-focus condition) did not demonstrate significant PE or RT disruptions. Furthermore, as shown in Table 3, the magnitudes of mean RT disruptions for the accuracy groups with the closest average accuracy rates (i.e., the low-accuracy group in the narrow-focus condition and the high-accuracy group in the wide-focus condition) are similar. This similarity indicates that the higher magnitude of the RT disruption measure in the narrow-focus relative to the wide-focus condition, when all subjects are considered together (see Table 1), is related to the higher accuracy rate of the narrow-focus condition.

These results reinforce the finding that perceptual requirements did not affect sequence learning. They indicate that the difference in magnitude of the mean RT disruptions in the wide-focus and narrow-focus conditions (see Table 1) is probably caused by a difference in accuracy rates. In particular, the difference in magnitude is greatly reduced when subjects with accuracy rates below 85% are excluded. These results also demonstrate that correct response selection and/or
execution may be important to implicit sequence learning. However, the degree of implicit learning was relatively small relative to previous research (i.e., compared to mean RT disruptions of approximately 100 to 200 ms observed in many sequence learning studies), even for the high-accuracy group in narrow-focus conditions which had a mean accuracy rate of 98%. Hence, low accuracy is probably not the only, or even the primary, cause of the low observed levels of sequence learning.

The Relationship Between Secondary Task Performance and Sequence Learning. Letter-set recall was scored by counting each letter recalled in the correct order (and multiplying the sum by two for the first version of the task) for a total of 90 possible points. Comparison of letter-set recall scores with recall on the working memory test revealed a common trend. Of those who performed the working memory test, seven who recalled strings of eight or nine elements had an average letter-set score of 80.5, twenty who recalled strings of six or seven elements had an average letter-set score of 71.45, and two who could recall only a five-element string had an average letter-set score of 60. The similar trends in these data suggest secondary task performance and working memory capacity may be linked. Consequently, the effect of secondary task performance on sequence learning was assessed. It was expected that better performers might make better use of working memory and therefore demonstrate better sequence learning to the extent that sequence learning utilizes working memory resources. If sequence learning does not utilize working memory resources, it may be less
affected by the secondary task for those subjects who found the task easiest.

Subjects were classified as good or excellent performers (poor performers were not considered in any analyses) if their recall scores were between 50 and 80 ($M = 69.54$, $SD = 7.23$, $n = 24$) or 80 and above ($M = 84.67$, $SD = 3.41$, $n = 30$), respectively. No effects of secondary task performance were yielded by ANOVAs in which block (Block 5 vs. 6), perceptual requirement (wide vs. narrow-focus), and performer type (good vs. excellent) were factors. The mean sequence learning demonstrated by excellent performers ($M = 28.1$, $SD = 57.28$, $n = 30$) was very similar to that of good performers ($M = 27.09$, $SD = 50.97$, $n = 24$). This result is not surprising because sequence learning was unaffected by workload in this experiment and it supports the conclusion that implicit sequence learning relies only minimally on attentional resources. To anticipate, however, the same null effects were found in Experiment 1b, where the workload factor did have an effect on sequence learning. Hence, although the workload manipulation was effective under the explicit learning conditions of Experiment 1b, secondary task scores were not sensitive indicators of individual differences in attentional resources, possibly because subjects emphasized primary over secondary task performance.

The Relationship Between Explicit Knowledge and Sequence Learning. Scores on the generation test were the largest number of sequence elements to be correctly reported in order by each subject, with a maximum score of 12. In addition, two recognition test
scores were also obtained. One was the mean difference between ratings of old and new sub-sequences with similar structural constraints (Recognition Score A) and the second was the mean difference between ratings of old and new sub-sequences with fewer structural constraints (Recognition Score B). Recognition scores could range from -3 to 3, with positive scores indicating that old sub-sequences were rated as more familiar than new sub-sequences.

Learners were classified as knowledgeable explicit learners (n = 14) if they reported trying to learn a pattern in the search task stimuli and also had a high generation test score (5 or higher) or two high recognition test scores (0.5 or higher). They were classified as knowledgeable implicit learners (n = 8) if they had a high generation test score or two high recognition test scores but reported that they did not try to learn any patterns in the stimuli. Implicit learners without explicit knowledge (n = 107) were those who, in addition to reporting that they had not tried to learn any stimulus patterns, did not meet the high explicit knowledge test score requirements. The generation and recognition test scores and the mean changes in RT associated with the removal of the target-orientation sequence in Block 6 are shown for each of the learner groups in Table 4.

Knowledgeable implicit learners were grouped with the implicit learners who lacked explicit knowledge for most analyses. The mean RT and PE disruptions of knowledgeable implicit learners (M = 27.56, SD = 39.48 and M = 1.6, SD = 2.5, respectively) were similar to those of the other implicit learners (M = 26.52, SD = 50.68 and M = 0.9, SD = 2.1, respectively). In contrast, the average RT
disruption of explicit learners was much higher ($M = 129.93$, $SD = 180.33$).

Table 4
Mean Explicit Knowledge Scores and Reaction Time Increases (in ms) Between Blocks 5 and 6 for Different Learner Groups in Experiment 1a

<table>
<thead>
<tr>
<th>Learner Type</th>
<th>Generation Score</th>
<th>Recognition Score A</th>
<th>Recognition Score B</th>
<th>RT Increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledgeable Explicit</td>
<td>8.54 (3.76)</td>
<td>1.13 (0.83)</td>
<td>1.35 (0.80)</td>
<td>129.93 (180.33)</td>
</tr>
<tr>
<td>Knowledgeable Implicit</td>
<td>5.11 (2.15)</td>
<td>0.38 (0.36)</td>
<td>0.83 (0.40)</td>
<td>27.56 (39.48)</td>
</tr>
<tr>
<td>Implicit</td>
<td>3.21 (1.61)</td>
<td>-0.06 (0.33)</td>
<td>0.36 (0.38)</td>
<td>26.52 (50.62)</td>
</tr>
</tbody>
</table>

Note. Standard deviations of scores and reaction time increases are in parentheses. Negative numbers indicate performance improvement, rather than disruption.

Nevertheless, knowledgeable implicit learners were grouped with explicit learners in order to compare the sequence learning of subjects who had acquired explicit knowledge (i.e., the knowledge group) to that of subjects who had not acquired explicit knowledge (i.e., the no-knowledge group) under the two workload and perceptual requirement conditions. Search task performance of the knowledge and no-knowledge groups across blocks and under different workload conditions is shown in Figure 4.

Generation and recognition scores were submitted to between-
subjects ANOVAs in which group (knowledge vs. no-knowledge), workload (dual vs. single-task), and perceptual requirement (wide vs. narrow-focus) were factors. A main effect of group on all three scores confirmed that the knowledge group had more explicit sequence knowledge than the no-knowledge group (all p's < .0001). There were no effects of workload or perceptual requirement, with the exception of a marginally significant effect of perceptual requirement on Recognition Score A (F(1,111) = 3.10, p = .081, MSE = 0.19), and an interaction of perceptual requirement with group for Recognition Score A, which was also marginally significant (F(1,111) = 3.41, p = .068, MSE = 0.19). ANOVAs of Score A for each group did not shed light on this interaction, as the effect of perceptual requirement was not statistically significant in either case. The interaction probably reflects the larger mean recognition score of the knowledge group under wide-focus conditions (M = 1.12) compared to under narrow-focus conditions (M = 0.68), and the absence of a difference between conditions for the no-knowledge groups (M = -0.07 and -0.05, respectively). There is not an obvious explanation of this difference, however, and generally speaking, workload and perceptual requirement conditions did not seem to affect the acquisition of explicit knowledge.
Figure 4. Mean reaction time (in ms) as a function of block for knowledge and no-knowledge groups under single-task and dual-task workload conditions in Experiment 1a.
Sequence learning by knowledge and no-knowledge groups under different workload conditions was examined by conducting ANOVAs in which block (Block 5 vs. 6), group (knowledge vs. no-knowledge), and workload (single vs. dual-task) were factors. Main effects of workload and group on RTs were found ($F(1,124) = 4.98$, $p = .027$, $\text{MSE} = 38,954$ and $F(1,124) = 14.89$, $p = .0002$, $\text{MSE} = 38,954$, respectively), and their interaction was marginally significant ($F(1,124) = 3.26$, $p = .073$, $\text{MSE} = 38,954$), reflecting the larger effect of workload on the RTs of the knowledge group (see Figure 4). There was also a main effect of block on RTs ($F(1,124) = 39.89$, $p = .0001$, $\text{MSE} = 2,826$) and an interaction of block with group ($F(1,124) = 11.60$, $p = .0009$, $\text{MSE} = 2,826$), which indicated that the RT increase between blocks (i.e., evidence of sequence learning) was larger for the knowledge ($M = 88.05$, $SD = 145.91$) than for the no-knowledge group ($M = 25.32$, $SD = 51.13$; see Figure 4). For PEs, there were main effects of group ($F(1,124) = 4.33$, $p = .04$, $\text{MSE} = 0.006$) and block ($F(1,124) = 10.02$, $p = .002$, $\text{MSE} = .001$), but as in the case of RTs, there was no effect of workload. These effects reflect the lower PE rate of the knowledge group ($M = 5$, $SD = 3.2$) compared to that of the no-knowledge group ($M = 7.5$, $SD = 6.1$) in Blocks 5 and 6 and the larger PE increase between blocks in the knowledge group ($M = 2.2$, $SD = 1.4$), compared to the no-knowledge group ($M = 1.1$, $SD = 4.3$).

As expected, the knowledge group learned the sequence better than did the no-knowledge group, as demonstrated by greater RT and PE disruptions as well as by better generation and recognition
test scores. However, there may have been a cost associated with the acquisition of explicit sequence knowledge in that the mean RT of the knowledge group was faster under single than dual-task conditions. A possible explanation of the workload effect on RTs as a function of knowledge group is that attentional resources used to acquire explicit knowledge reduced the spare attentional capacity relative to that of the no-knowledge group, making the workload manipulation more effective. Alternatively, the workload effect may be an artifact of the small sample sizes of the workload conditions of the knowledge group. An imbalance between the number of knowledgeable implicit and explicit learners assigned to each workload condition can at least be ruled out as a potential artifact, because about half of the subjects in each condition were knowledgeable implicit learners. Nevertheless, this workload effect may not be meaningful.

Search Task Learning. Analyses were performed on RTs and PEs to examine the effects of workload and perceptual requirement on search task performance prior to and after interruption of the sequence in target orientations (in Block 6). Mean RTs across all blocks of trials are shown in Figure 3. Blocks 1 through 5, Blocks 6 and 7, and Blocks 8 and 9 were submitted to separate ANOVAs with the factors workload (single vs. dual-task), perceptual requirement (wide vs. narrow-focus), and block. The Geisser-Greenhouse correction was used to evaluate repeated measures.

The ANOVAs revealed main effects of perceptual requirement that were indicative of lower PEs and faster RTs in narrow than in wide-focus conditions for all three sets of blocks (all $p$'s < .0001).
No other effects were significant for PE. For RT, there were no other effects in Blocks 6 and 7, however, in the other two sets of blocks, there was a main effect of block (both p's < .0004). In Blocks 1 through 5, the main effect of block was mediated by an interaction with perceptual requirement ($F(4,444) = 22.65, p = .0001, \text{MSE} = 2,065$). Figure 3 shows that this interaction is probably the result of a steeper learning curve across these blocks in the wide-focus relative to the narrow-focus condition. In Blocks 8 and 9, there also was a marginally significant effect of workload ($F(1,111) = 2.94, p = .09, \text{MSE} = 23,589$) and a Block x Workload interaction ($F(1,111) = 4.14, p = .044, \text{MSE} = 994$), which reflects a larger workload effect in Block 8, the block in which the sequence in target orientations resumed, than in Block 9. This seems to be caused by a lag in the recovery of RT performance once the sequence resumed with a dual-task, but not a single-task, workload, particularly under wide-focus conditions (see Figure 3).

**Set-Size Effects on Search Task Performance.** Set size was analyzed to see if subjects used a distributed attention search strategy, as was expected. In the narrow-focus condition, subjects were expected to use a distributed-attention search strategy to find the target within a 12 or 16-stimulus array. In wide-focus conditions, subjects were expected to use distributed attention both to find the target within the 4 or 8-stimulus sets and to determine its orientation. The absence of an RT increase when array size is increased is regarded as evidence of distributed-attention search. Statistical analyses of set size in narrow-focus and wide-focus conditions,
respectively, indicated that distributed attention was used in target search in both conditions. In the wide-focus condition, however, attention seems to have been distributed over the target rectangle once it was found, whereas it seems to have been distributed over the entire search array in the narrow-focus condition.

The PEs and RTs for the search task in each perceptual requirement condition were submitted to separate ANOVAs with block (Blocks 1 through 9) and set size (12 vs. 16 array elements in narrow-focus conditions and 4 vs. 8 subgroup elements in wide-focus conditions) as repeated-measures factors and workload (single vs. dual-task) as a between-subjects factor. There were no effects of set size in the narrow-focus condition, confirming that targets were located using distributed visual attention. However, in the wide-focus condition, main effects of set size on RTs ($F(1,126) = 54.88, p = .0001, \text{MSE} = 165,726$) and PEs ($F(1,126) = 30.80, p = .0001, \text{MSE} = 0.034$) indicated that responses were faster and more accurate for set sizes of four compared to eight. Mean RT and PE were 176 ms and 6% higher, respectively, for a set size of four than of eight. These differences are not predicted by a focused-attention search model. In particular, the effect of set size on RTs is in the opposite direction of the predicted effect.

A follow-up study showed that the 176-ms difference between subset sizes was a consequence of the time required to locate a set of four elements compared to the time taken to locate a set of eight elements. In this follow-up study, ten subjects performed 100 practice trials, followed by 240 test trials, of a search task in which
they found a set of same-color bars (i.e., in the target rectangle) and identified the color of the bars. A repeated measures ANOVA with target color and size as factors revealed that mean RT was 158 ms longer for subgroups of four than of eight elements \((F(1,72) = 19.29, p = .0001, \text{MSE} = 55,624)\). Array size did not affect PEs, however, which suggests that the mean PE difference of 6% in the present study is related to identification of the unique orientation within the target rectangle. Apparently the target does not "pop-out" as much when it contrasts with three, rather than seven, elements of a different orientation. It is difficult to explain how this PE difference might have occurred under focused-attention search conditions. Hence, the difference is suggestive of the use of distributed attention for processing the same-color sets.

The results of ANOVAs of set-size effects in the present experiment also demonstrated a main effect of block on RTs in narrow-focus conditions \((F(8,1096) = 173.18, p = .0001, \text{MSE} = 3,546)\), on PEs in wide-focus conditions \((F(8,1008) = 4.74, p = .0002, \text{MSE} = 0.005)\) and on RTs in wide-focus conditions \((F(8,1008) = 344.97, p = .0001, \text{MSE} = 4,031)\), in which case block also interacted with size \((F(8,1008) = 6.65, p = .0001, \text{MSE} = 4,031)\). Block effects reflect performance improvements across blocks and the Block x Size interaction is probably the result of the larger RT decrease across blocks for a set size of four \((M = 364.66)\) compared to a set size of eight \((M = 296.91)\).
they found a set of same-color bars (i.e., in the target rectangle) and identified the color of the bars. A repeated measures ANOVA with target color and size as factors revealed that mean RT was 158 ms longer for subgroups of four than of eight elements ($F(1,72) = 19.29$, $p = .0001$, $MSE = 55,624$). Array size did not affect PEs, however, which suggests that the mean PE difference of 6% in the present study is related to identification of the unique orientation within the target rectangle. Apparently the target does not "pop-out" as much when it contrasts with three, rather than seven, elements of a different orientation. It is difficult to explain how this PE difference might have occurred under focused-attention search conditions. Hence, the difference is suggestive of the use of distributed attention for processing the same-color sets.

The results of ANOVAs of set-size effects in the present experiment also demonstrated a main effect of block on RTs in narrow-focus conditions ($F(8,1096) = 173.18$, $p = .0001$, $MSE = 3,546$), on PEs in wide-focus conditions ($F(8,1008) = 4.74$, $p = .0002$, $MSE = 0.005$) and on RTs in wide-focus conditions ($F(8,1008) = 344.97$, $p = .0001$, $MSE = 4,031$), in which case block also interacted with size ($F(8,1008) = 6.65$, $p = .0001$, $MSE = 4,031$). Block effects reflect performance improvements across blocks and the Block x Size interaction is probably the result of the larger RT decrease across blocks for a set size of four ($M = 364.66$) compared to a set size of eight ($M = 296.91$).
Summary of Experiment 1a Results. The central finding of this experiment is implicit sequence learning during performance of a relatively complex task under both distributed and focused visual attention conditions and under both single-task and dual-task workload conditions. This indicates that implicit learning can benefit performance in complex task environments.

The mean RT and PE disruptions between Blocks 5 and 6 were not statistically different for the two perceptual requirement conditions, and the slight difference in the magnitude of RT disruptions all but disappeared when groups of subjects with similar accuracy rates were compared (see Table 3). The absence of a sequence learning difference between perceptual requirement conditions seems to indicate that the allocation of less visual attention to targets when attention is distributed, instead of focused, does not affect how well sequential patterns of target stimuli are learned. With respect to complex task performance, this means that even if a distributed visual load restricts the use of focused visual attention, stimulus patterns should still be learned implicitly.

A possible explanation of the absence of a sequence learning difference between perceptual requirement conditions is that initial spatial representations of targets that could have been affected by perceptual requirements were quickly translated into symbolic or verbal representations that were not affected. Another explanation is that implicit learning benefits were due to the retrieval of past instances, in which case perceptual requirements might affect the nature of stimulus representations only if the visual attention strategy
were altered. A change in strategy might cause a mismatch between perceptual retrieval cues and stored representations created using another attention strategy which would impair instance retrieval and therefore implicit learning benefits, as well. In addition, perceptual requirement effects might be observed if series of stimuli that are represented as spatial images can be learned.

The absence of an effect of perceptual requirement conditions indicates that only series of symbolic or verbal stimulus codes may be learned. This implicates response selection, which involves the translation of stimuli into such response codes, as the locus of implicit learning in this experiment. With respect to this point, analyses that took overall search-task accuracy rates into account showed that response accuracy is an important factor in sequence learning, thereby indicating that response selection (i.e., S-R mapping) and/or execution processes is a locus of implicit sequence learning. A response execution locus has been all but ruled out (e.g., Cohen et al., 1990; Fendrich et al., 1991), hence, a response-selection locus of implicit sequence learning is the most likely basis of the present effects. If response selection is essential to implicit sequence learning, then series of stimuli should be learned unless they are not assigned to responses.

This experiment also demonstrated that implicit learning may require only minimal attentional resources. Notably, secondary task performance did not affect the learning of ambiguous associations among sequence elements, a form of learning hypothesized to rely on attentional resources (e.g., Cohen et al, 1990; Curran & Keele,
1992). Nonetheless, in wide-focus conditions, workload seemed to affect search task RTs when the sequence was re-introduced in Block 8. Thus, an effect of workload cannot be entirely ruled out.

Not surprisingly, the performance of subjects who acquired explicit sequence knowledge, was more disrupted by the switch to a random presentation than that of implicit learners with little or no explicit sequence knowledge (i.e., no-knowledge group members). The additional finding that secondary task performance might have interfered more with the search task performance of subjects with explicit knowledge was not expected, although it might be an artifact, as noted above.

The absence of a workload effect on the sequence learning of subjects with explicit knowledge is also noteworthy. Explicit learning is thought to utilize significant attentional resources and, consistent with this, it can be suppressed by a secondary tone-counting task (e.g., Curran & Keele, 1992). The absence of a workload effect in this experiment might indicate that sequence learning, in general, requires few attentional resources. Experiment 1b, in which subjects are explicitly instructed to learn the sequence, will address this issue.

Analysis of Visual Attention Strategies. Different search instructions were used in wide-focus and narrow-focus conditions to manipulate visual attention (i.e., to cause distributed or focused attentional processing of the target). This section describes exploratory analyses that may shed light on the nature of the visual attention strategies used to perform the search task and hence, on the
effectiveness of the instructional manipulation. Specifically, these analyses are of an S-R compatibility effect known as the Simon effect (see Simon, 1990). The Simon effect is the RT increase frequently observed when stimuli and responses are spatially incompatible relative to when they are spatially compatible, despite the irrelevance of their spatial locations to task performance. In the present experiment, stimuli and responses were spatially incompatible when the target appeared in a left column of the search array and the correct response key was on the right end of the row of response keys, and vice versa. They were compatible when both the target and the correct response key were located on the same side.

For the compatibility analyses, only responses using the extreme left and right keys (i.e., the keys assigned to the target orientations 75 deg left and right) made to targets appearing in the extreme left and right columns of the search array were considered. Also, explicit learners (and not poor secondary task performers) were excluded because if the target orientation sequence is learned explicitly, keypresses can be anticipated and hence, visual attention is not required.

Compatibility effects were evaluated by comparing RTs and PEs in compatible trials with those in incompatible trials. It was anticipated that compatibility effects might be smaller in wide-focus than in narrow-focus conditions because a wider spotlight beam would require less movement to reach a target in an extreme left or right column. This is predicted by a spatial-orienting explanation of the Simon effect (e.g., Nicoletti & Umiltà, 1994; Stoffler, 1991).
Further, it was anticipated that an added workload might affect visual attention, either by making a narrow spotlight of attention more likely (e.g., Williams, 1988) or less likely (e.g., Ste-Marie & Jacoby, 1993) than a wider spotlight. Again, differences in spotlight size under different workload conditions might translate into differences in the size of the compatibility effect. To evaluate these hypotheses, data from Blocks 1 through 5, Blocks 6 and 7 (in which the feature sequence was replaced with a random pattern), and Blocks 8 and 9 were submitted to separate ANOVAs in which perceptual requirement (wide vs. narrow focus), compatibility (compatible vs. incompatible locations), and block were factors.

The factors perceptual requirement, workload, and block were assessed in the analyses reported above and hence, will only be mentioned with respect to their interactions with compatibility. To summarize the main results of the compatibility analyses, compatibility effects on RTs were reduced under dual-task compared to single-task conditions in later blocks of trials, but were not affected by perceptual requirement or block. In addition, compatibility effects on PEs were greater under wide-focus than narrow-focus conditions, seem to have been greater under single-task than dual-task conditions in Blocks 1 through 5, and were not affected by block.

A main effect of compatibility on RTs was found in Blocks 1 through 5 ($F(1,118) = 73.1$, $p = .0001$, $MSE = 3,272$), and the effect was similar in the other two sets of blocks (both $p$'s = .0001). Under single-task conditions, the mean compatibility effect for RTs was 71
ms in Blocks 1 through 5, compared to 46 ms in Blocks 6 and 7 and only 29 ms in Blocks 8 and 9. In contrast, the mean compatibility effect for RTs under dual-task conditions was 55 ms in Blocks 1 through 5, 61 ms in Blocks 6 and 7, and 65 ms in Blocks 8 and 9. Hence, there was a tendency for compatibility effects on RTs to decrease across blocks under single-task, but not dual-task, conditions. In support of this trend, an interaction of compatibility with workload was found only for Blocks 8 and 9 ($F(1,118) = 5.99$, $p = .016$, MSE = 3,339), indicating that the difference between dual-task and single-task conditions was statistically significant only in these final blocks of trials.

According to the spatial-orienting explanation of the Simon effect, the decrease in compatibility effects might have occurred because subjects tended to switch to a strategy that utilized a wider attentional spotlight as they gained practice in the search task, but only when they were not required to perform the secondary rehearsal task. This is consistent with research by Williams (1988) showing that focused visual attention is more likely to be used under dual-task demands than under single-task demands. However, the secondary task used by Williams (1988) was visual and so his results also may be interpreted to mean that attention is more likely to be focused as visual load increases, which has been found by others (e.g., Lavie, 1995). In contrast, the secondary task in the present research was nonvisual, but still seemed to encourage the use of focused visual attention.

For PEs in Blocks 1 through 5, there was a main effect of
compatibility ($F(1,118) = 26.65$, $p = .0001$, MSE = 0.002), and a Compatibility x Perceptual Requirement interaction ($F(1,118) = 4.3$, $p = .04$, MSE = 0.002), and similar effects were found for PEs in Blocks 8 and 9 ($p$'s < .002). The Compatibility x Perceptual Requirement interactions were caused by larger compatibility effects on PEs in wide-focus conditions ($M = 4.2\%$ and 4.6\% in Blocks 1 through 5 and Blocks 8 and 9, respectively) than in narrow-focus conditions ($M = 1.7\%$ and 0.02\%, respectively). In addition, there was a marginally significant interaction of compatibility with workload for PEs in Blocks 1 through 5 ($F(1,118) = 3.54$, $p = .062$, MSE = .002), indicating that compatibility effects on PEs were larger under single-task than dual-task conditions in these blocks. However, this pattern was not found in the other two sets of blocks. Hence, workload did not appear to influence compatibility effects on PEs once subjects became well-practiced. For PE in Blocks 6 and 7, no compatibility effects were found.

Contrary to expectations, these results reveal that S-R compatibility tended to affect RTs similarly in wide-focus and narrow-focus conditions. Compatibility effects on RTs tended to be smaller in the wide-focus (mean compatibility effect for all blocks = 49.33 ms) than in the narrow-focus condition (mean compatibility effect for all blocks = 59.67 ms), as predicted, but the difference was not statistically significant. Furthermore, the difference did not exist under dual-task conditions, but instead existed only under single-task conditions, reflecting a faster and larger decrease in mean compatibility effects on RTs for single-task performance across sets.
of blocks under wide-focus, compared to narrow-focus, conditions.

Also contrary to expectations, a difference between compatibility effects on PEs was found such that the compatibility effect was larger in the wide-focus than in the narrow-focus condition. The larger compatibility effect in the wide-focus condition is probably related to the grouping of stimuli within the target quadrant. In this condition, subjects were expected to focus on the target rectangle, which contained either three or seven distractors of the same orientation, in addition to the uniquely-oriented target. When target location was incompatible with the location of the correct response key, but, along with the distractor locations in the target rectangle, it was compatible with the location of the response key that mapped onto those distractors' orientation, subjects' tendency might have been to respond to the distractor, instead of the target, orientation. In other words, a flanker effect (e.g., Eriksen & Eriksen, 1974) may have occurred, whereby the orientations of flanking distractors interfered with the processing of target orientations. This was especially likely because distractor stimuli in the target quadrant all shared the same orientation, possibly making that orientation more perceptually salient than the target orientation.

In conclusion, these analyses demonstrated a larger compatibility effect on PEs in the wide-focus than in the narrow-focus condition. If the larger compatibility effect in the wide-focus condition was due to interference from flanking distractor orientations, as suggested above, this would mean that visual attention was distributed across stimuli in the target rectangles and that distributed attention was
therefore allocated to targets in that condition, as intended. Unfortunately, it is not possible to distinguish between the perceptual strategies of the wide-focus and narrow-focus search tasks based on this result because characteristics of the narrow-focus search task do not permit an evaluation of whether distractor orientations were processed.

These analyses also indicated that compatibility-related errors may have been more likely under single-task, relative to dual-task, conditions during early learning stages. Further, they showed that workload may influence the type of visual attention strategy utilized and, in particular, that multiple-task workloads may discourage the use of distributed visual attention in task performance.

**Experiment 1b**

This experiment was performed to contrast explicit learning with the implicit learning observed in Experiment 1a. In particular, performance of a secondary letter-set rehearsal task was expected to affect explicit more than implicit learning, as has been demonstrated using a secondary tone-counting task (e.g., Curran & Keele, 1992). In addition, explicit learning is usually equivalent or superior to implicit learning, depending on the ambiguity and complexity of both the information to be learned and the explicit instructional set (Berry, 1994). However, depending on the amount of learning that can be achieved using an implicit learning mode, an implicit mode may be chosen over an explicit one in certain contexts (e.g., when there is too much information to learn explicitly within a given time frame), even if it is quantitatively inferiority to explicit learning.
Method

Facilities. Research facilities were identical to those of Experiment 1a.

Participants and Design. Participants were 64 male and 14 female volunteers from the USAF basic training program at LAFB. Seven reported color-deficient vision or made at least four color identification errors on a color test. Six reported a left-hand preference for writing or throwing. Fifteen reported left-eye dominance. Participants were each randomly assigned to either the single or dual-task workload condition. Within-subject factors were set size (four vs. eight bars in the target rectangle) and block (nine blocks of 120 trials). Other details were the same as in Experiment 1a.

Stimuli. The stimuli were identical to those used in the wide-focus condition of Experiment 1a.

Procedure. The procedure was identical to that of Experiment 1a except for the changes noted below. After practice trials, participants were told that target orientations would follow a repeating sequence in all but the sixth and seventh blocks of trials and that they should try to learn the sequence in order to optimize their search task performance and because they would later be asked to reproduce it. Subjects performed the same search task performed in the wide-focus condition of Experiment 1a. The secondary task performed in the dual-task condition was identical to the second version of the letter-set rehearsal task used in Experiment 1a (i.e., letters sets were recalled at the middle and end of each block).
Results and Discussion

The data of seven participants were lost due to program malfunctions and experimenter error. Of the remaining subjects, 58 met the criterion accuracy rate of 75% or better, and five of these subjects were excluded from analyses based on poor secondary task scores. Performance by participants with color-deficient vision (n = 4) or who were left-handed (n = 8) did not differ statistically or descriptively from performance by the others. Nor did the performance of males (n = 46) and females (n = 7) differ. Left-eye dominant subjects (n = 10) performed the search task 146 ms more slowly than right-eye dominant subjects, on average (F(1,51) = 7.95, p = .007, MSE = 30,474), but this difference has no obvious explanation and did not occur in other experiments. Hence, the data of these subjects were submitted together to the analyses described below. For these 53 subjects, trials were discarded if the RT was less than 150 ms or if a response was not made before the response period expired (2.1% of trials), and incorrect trials were excluded from RT analyses (mean PE = 9.1%).

Sequence Learning. Sequence learning was quantified as the mean changes in RTs and PEs between Blocks 5 and 6, caused by replacement of the target orientation sequence with a randomized order. The mean RT and PE disruptions for each of the workload conditions are shown in the first column of Tables 5 and 6, respectively. Sequence learning was assumed to be explicit because subjects were instructed to intentionally learn the target orientation sequence. Analyses of sequence learning mode that are reported
below compare explicit sequence learning in the present experiment with implicit sequence learning in the wide-focus conditions of Experiment 1a. Figure 5 shows mean RTs across all nine blocks of trials and the disruptions in mean RT caused by the switch to a randomized feature sequence in the different sequence learning mode and workload conditions.

Table 5
Mean Increases in Reaction Time (in ms) from Block 5 to Block 6 for Different Types of Sequence Associations in Experiment 1b

<table>
<thead>
<tr>
<th>Condition</th>
<th>Sequence Associations</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Unique</td>
<td>Ambiguous</td>
</tr>
<tr>
<td>Single-Task</td>
<td>86.19</td>
<td>94.31</td>
<td>83.63</td>
</tr>
<tr>
<td>n = 25</td>
<td>(186.59)</td>
<td>(182.77)</td>
<td>(192.68)</td>
</tr>
<tr>
<td>Dual-Task</td>
<td>41.90</td>
<td>45.77</td>
<td>40.87</td>
</tr>
<tr>
<td>n = 28</td>
<td>(114.02)</td>
<td>(145.13)</td>
<td>(110.59)</td>
</tr>
</tbody>
</table>

Note. Standard deviations of reaction time increases are in parentheses.

ANOVAAs were performed to assess sequence learning with the factors block (Block 5 vs. 6), workload (single vs. dual-task), and learning mode (implicit vs. explicit). Results are given in an ANOVA table in Appendix D. Evidence of sequence learning included a marginally significant effect of block on PEs (F(1,106) = 2.96, p = .088, MSE = 0.003) and a main effect of block on RTs (F(1,106) = 15.19, p = .0002, MSE = 6,640). No other effects were found for PE, but for RT, there were marginally significant effects
of workload ($F(1, 106) = 3.32, p = .071, MSE = 30,788$) and learning mode ($F(1, 106) = 3.35, p = .07, MSE = 30,788$), and a Block x Learning Mode interaction that approached significance ($F(1, 106) = 3.65, p = .059, MSE = 6,640$). The Block x Learning Mode interaction was related to the larger RT disruption between Blocks 5 and 6 for the explicit learning mode than for the implicit learning mode (see Figure 5). The main effects of workload and learning mode reflected a tendency for faster RTs in single-task conditions and with the explicit learning mode.

Table 6
Mean Increases in Percent Errors from Block 5 to Block 6 for Different Types of Sequence Associations in Experiment 1b

<table>
<thead>
<tr>
<th>Condition</th>
<th>Sequence Associations</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Unique</td>
</tr>
<tr>
<td>Single-Task</td>
<td>1.9</td>
<td>3.2</td>
</tr>
<tr>
<td></td>
<td>(10.3)</td>
<td>(10.7)</td>
</tr>
<tr>
<td>Dual-Task</td>
<td>0.4</td>
<td>3.5</td>
</tr>
<tr>
<td></td>
<td>(6.6)</td>
<td>(8.4)</td>
</tr>
</tbody>
</table>

Note. Standard deviations of percent error increases are in parentheses. Negative numbers indicate performance improvement, rather than disruption.
Figure 5. Mean reaction time (in ms) as a function of block under different workload and instruction conditions in Experiment 1b.
Although the three-way interaction of block, workload, and learning mode was not statistically significant, Figure 5 shows that the mean RT increase between Blocks 5 and 6 tended to be greater in single-task conditions when learning was explicit than when it was implicit. This is also indirectly supported by the marginally significant interaction of block and learning mode in single-task conditions ($F(1,57) = 3.53, p = .065$, MSE = 8,924), but not in dual-task conditions.

These results show that explicit sequence learning leads to better performance than implicit sequence learning, but that explicit learning tends to be more affected by workload. Sequence learning, as measured by the RT disruptions caused by the switch to random presentations, was approximately four times as great for explicit compared to implicit learning under single-task workload conditions and was approximately twice as high under dual-task workload conditions (see Table 5). An examination of individual subject RTs revealed that a similar number of subjects demonstrated sequence learning in implicit and explicit learning mode conditions. Increases in mean RT between Blocks 5 and 6 were found for 67% of subjects in the explicit conditions and 65% of subjects in the implicit condition. This means that subjects who demonstrated sequence learning under explicit learning conditions tended to learn the sequence better than implicit learners, and not that there was a difference in the number of explicit and implicit learners who demonstrated sequence learning.
Unique and Ambiguous-Association Learning. Mean RT and PE disruptions associated with the learning of unique and ambiguous-associations are shown in the second and third columns of Tables 5 and 6. The results of ANOVAs performed to assess the learning of unique and ambiguous associations in the target orientation sequence are given in Appendices E and F, respectively. The results were similar to those found in the sequence learning analyses described above. However, they additionally suggested that ambiguous-association learning was improved more than unique-association learning by the use of an explicit mode, relative to the use of an implicit mode. Specifically, they revealed a Block x Learning Mode interaction for ambiguous-association RTs ($p = .041$), but not for unique-association RTs. Table 5 shows that increases in mean RT for unique and ambiguous associations were similar when learning was explicit; in contrast, inspection of Table 1 reveals that mean RT increases were noticeably larger for unique than for ambiguous associations when learning was implicit. Additional evidence that ambiguous-association learning was benefitted more than unique-association learning by an explicit learning mode is a marginally significant effect of learning mode on ambiguous-association RTs ($p = .06$), but not on unique-association RTs. Mean RT for ambiguously-associated sequence elements was 44 ms faster in explicit than in implicit learning mode conditions during Blocks 5 and 6. In addition, this RT advantage for explicit learning increased across blocks, from 14 ms in Block 1 to 67 ms in Block 5. This trend does not occur for unique associations, suggesting that explicit
learners learned ambiguous, but not unique, associations more quickly than implicit learners.

The Effects of Search Task Accuracy on Sequence Learning. As in Experiment 1a, the importance of response accuracy to sequence learning was assessed. Subjects were assigned to the high accuracy group if their accuracy rate was 91% or better ($M = 0.946$, $SD = 0.036$, $n = 28$) and to the low accuracy group if their accuracy rate was between 75 and 91% ($M = 0.865$, $SD = 0.08$, $n = 25$). ANOVAs with accuracy group (high vs. low), workload (single vs. dual-task), and block (Block 5 vs. 6) as factors yielded a main effect of accuracy group on RTs ($F(1,49) = 9.45$, $p = .003$, $MSE = 30,427$) and a Block x Accuracy Group interaction ($F(1,49) = 5.52$, $p = .023$, $MSE = 11,010$). ANOVAs performed on the RTs of each accuracy group revealed that the 111-ms mean RT disruption of the high accuracy group, but not the 14-ms mean RT disruption of the low accuracy group, was statistically significant ($F(1,26) = 8.83$, $p = .006$, $MSE = 19,542$), indicating that only subjects with high accuracy rates tended to learn the target-orientation sequence. No effects on PEs were found in these analyses, with the exception of the effect of accuracy group ($p = .0001$), which was to be expected.

Comparison of sequence learning in the two accuracy groups reinforced the finding of Experiment 1a that response accuracy affects sequence learning. An alternate explanation of learning differences between accuracy groups in the present experiment is that explicit learning produced higher response accuracy than implicit learning (because the sequence is better learned). Because
some subjects chose to use an implicit learning strategy despite instructions, the high and low accuracy groups may represent primarily explicit and implicit learners, respectively. Thus, it is possible that in this experiment, response accuracy and sequence learning affected one another. This explanation is not consistent with explicit knowledge test scores of the high and low accuracy groups, however, which were approximately equal.

The Relationship Between Secondary Task Performance and Sequence Learning. Letter-set recall was scored and subjects were classified as good \((M = 68, SD = 9.33, n = 9)\) or excellent \((M = 84.88, SD = 3.07, n = 16)\) secondary task performers as in Experiment 1a. As was the case in Experiment 1a, statistically significant differences were not found between the sequence learning or search task performance of good and excellent performers. In contrast to Experiment 1b, however, sequence learning in the present experiment was affected by workload. Thus, secondary task scores were not reliable indicators of individual differences in the attentional resources dedicated to secondary task performance, as noted in the results section of Experiment 1a.

The Relationship Between Explicit Sequence Knowledge and Sequence Learning. Generation and recognition test scores were calculated and subjects classified as knowledgeable explicit learners \((n = 15)\), knowledgeable implicit learners \((n = 6)\), and implicit learners without explicit knowledge \((n = 32)\) in the same manner as in Experiment 1a. The number of subjects in each group indicates that despite instructions to try to learn the repeating target-
orientation sequence, many subjects did not do so. Mean generation and recognition test scores and increases in mean RT associated with the removal of the target-orientation sequence are shown for each group in Table 7.

Table 7
Mean Explicit Knowledge Scores and Reaction Time Increases (in ms) Between Blocks 5 and 6 for Different Learner Groups in Experiment 1b

<table>
<thead>
<tr>
<th>Learner Type</th>
<th>Generation Score</th>
<th>Recognition Score A</th>
<th>Recognition Score B</th>
<th>RT Increase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledgeable Explicit</td>
<td>9.29 (2.52)</td>
<td>0.48 (0.96)</td>
<td>0.76 (1.15)</td>
<td>180.78 (124.15)</td>
</tr>
<tr>
<td>Knowledgeable Implicit</td>
<td>3.51 (1.05)</td>
<td>0.72 (0.16)</td>
<td>0.76 (0.41)</td>
<td>36.41 (30.97)</td>
</tr>
<tr>
<td>Implicit</td>
<td>3.34 (1.18)</td>
<td>0.01 (0.31)</td>
<td>0.27 (0.48)</td>
<td>16.59 (50.68)</td>
</tr>
</tbody>
</table>

Note. Standard deviations of test scores and reaction time increases are in parentheses.

As in Experiment 1a, knowledgeable implicit learners were grouped with explicit learners in order to compare knowledge (i.e., knowledgeable implicit and explicit-learner) and no-knowledge (i.e., implicit-learner) groups of subjects in terms of their explicit knowledge and sequence learning measures. Generation and recognition scores of subjects in explicit learning conditions were submitted to ANOVAs in which group (knowledge vs. no-knowledge) and workload (dual vs. single-task) were factors. A
main effect of group in each ANOVA confirmed that the knowledge group had more explicit sequence knowledge than the no-knowledge group (all p's < .02). No effects of workload were found, indicating the workload did not affect explicit knowledge acquisition.

Mean RTs of knowledge and no-knowledge groups under different workload conditions is shown in Figure 6. This figure shows a steeper learning trend across Blocks 1 through 5, in addition to a larger RT disruption between Blocks 5 and 6, under single-task than under dual-task conditions for subjects who acquired explicit knowledge.

To investigate the effects of explicit knowledge on sequence learning, 2 x 2 x 2 (Block x Group x Workload) ANOVAs were performed. For RT, there were main effects of group (F(1,49) = 9.11, p = .004, \( \text{MSE} = 30,672 \)) and block (F(1,49) = 12.06, p = .001, \( \text{MSE} = 30,672 \)), mediated by their interaction (F(1,49) = 7.27, p = .01, \( \text{MSE} = 10,673 \)). The Group x Block interaction reflected an effect of block in the knowledge group (F(1,19) = 6.46, p = .02, \( \text{MSE} = 25,483 \)) that was larger than the marginally significant effect of block in the no-knowledge group (F(1,30) = 3.25, p = .082, \( \text{MSE} = 1,293 \)). A main effect of workload was not found, nor were any main effects on PEs found, although there was a three-way interaction for PE (F(1,49) = 6.36, p = .022, \( \text{MSE} = 0.004 \)). This interaction reflects a PE disruption in the knowledge group (\( \text{M} = 5.7 \)), but not in the no-knowledge group (\( \text{M} = -1.4 \)) under single-task conditions. In dual-task conditions, the PE disruption was small for both groups (\( \text{M} = 2.5 \) and \( \text{M} = 1.8 \), respectively).
Figure 6. Mean reaction time (in ms) as a function of block for knowledge and no-knowledge groups of subjects instructed to learn explicitly under single-task and dual-task workload conditions in Experiment 1b.
The PE results indicate that the most sequence learning was achieved by the knowledge group under single-task conditions. The RT results also revealed more sequence learning by the knowledge group than by the no-knowledge group and, although the effect was not statistically significant, Figure 6 shows that the mean RT disruption of the knowledge group is larger under single-task than under dual-task conditions.

**Search Task Learning.** Search task RTs and PEs were analyzed to examine the effects of workload and learning mode prior to and after interruption of the sequence in target orientations in Block 6. Mean RTs across all nine blocks of trials are shown in Figure 5. Blocks 1 through 5, Blocks 6 and 7, and Blocks 8 and 9 were submitted to separate ANOVAs with the factors workload (single vs. dual-task), learning mode (implicit vs. explicit), and block. A main effect of block on RTs and PEs in Blocks 1 through 5 and in Blocks 8 and 9 reflected a decrease in RTs and PEs across those blocks of trials (all p's < .04). In addition, there was a main effect of learning mode on RTs in Blocks 8 and 9 (F(1, 106) = 4.75, p = .032, MSE = 43,880), indicating that explicit learners performed better than implicit learners, and there was a similar trend for RTs and PEs in Blocks 1 through 5 (both p's < .08). There was also a marginally significant effect of workload on RTs in Blocks 6 and 7 and in Blocks 8 and 9 (both p's < .10), which can be seen in Figure 5 as a tendency for RTs to be slower under dual-task, compared to single-task, conditions. For PE, there was not a main effect of workload, but there was a three-way interaction of block, workload, and
learning mode in Blocks 8 and 9 ($F(1, 106) = 4.99, p = .028, \text{MSE} = 0.005$), which seemed to reflect the larger increase in PEs across the last two blocks of trials under single-task relative to dual-task conditions when learning was explicit (mean PE increases were 5.1% and 0.3% in single-task and dual-task conditions, respectively), but not when it was implicit.

These analyses found that: Search task performance improved across the nine blocks of trials; subjects in explicit learning mode conditions tended to be faster and more accurate than subjects in implicit learning mode conditions; and a dual-task workload seemed to slow RTs. Also, a Block x Workload interaction for Blocks 8 and 9 like the one observed in Experiment 1a was not found in this experiment, indicating that a dual-task workload did not result in a lag in the time to return to the performance level achieved prior to replacement of the sequence with a random presentation once the sequence was reintroduced when learning was explicit.

**Set-Size Effects on Search Task Performance.** The size of stimulus sets within target rectangles was analyzed to determine if subjects used a distributed attention search strategy. As in the wide-focus conditions of Experiment 1a, subjects were expected to use distributed attention both to find the target within the target rectangle and to determine its orientation. Therefore, there should not be an effect of set size on performance.

ANOVAAs were performed on PEs and RTs with the repeated-measures factors block (Blocks 1 - 9) and set size (four vs. eight) and the between-subjects factor workload (single vs. dual-task). There
was a main effect of set size on RTs ($F(1,110) = 52.43, p = .0001, MSE = 151,575$), mediated by its interaction with block ($F(1,880) = 3.30, p = .018, MSE = 8,189$). Mean RT was 177 ms faster for sets of eight than of four and the difference decreased from 239 ms in Block 1 to 144 ms in Block 9. There was also a main effect of set size on PEs ($F(1,110) = 23.57, p = .0001, MSE = 0.027$). Mean PE was 5% higher for the set size of four than of eight.

These results are similar to those found in the analyses of set size performed on the data from Experiment 1a. Findings of the follow-up study described in the Experiment 1a results section suggest that, in the present experiment, distributed attention was used to identify target orientation once the target rectangle was found. Specifically, the 177-ms difference between set sizes can be explained as the difference in time spent to locate a target rectangle containing four versus eight elements, not in time spent to search for the target within the target rectangle. In addition, as noted in the results section of Experiment 1a, the difference in PE rates can be explained in terms of a distributed-attention model as a difference in how much the unique orientation of the target "popped out" of a background of three versus seven distractors, but is difficult to explain in terms of a focused attention search model.

**Summary of Experiment 1b Results.** This experiment demonstrated that explicit learning of a target-feature/response sequence is superior to implicit sequence learning in a relatively complex search task. Measures of sequence learning in the form of mean RT and PE disruptions associated with sequence removal were
91% and 53% larger, respectively, for explicit learners than for implicit learners. However, this advantage was greatly diminished under dual-task performance conditions. Explicit sequence learning was impaired by dual-task performance, resulting in mean RT and PE disruptions that were 45% and 50% larger, respectively, than those of implicit learners in dual-task conditions.

Despite instructions to try to learn the sequence in target orientations, approximately 72% of subjects did not do so. Presumably, this was because learning and performance of the primary search task demanded significant resources. Sequence learning by these subjects, in terms of the RT increase when target orientations switched to a random presentation ($M = 19.72$ ms), was similar in magnitude to sequence learning by subjects in implicit learning mode conditions who had not been told about the existence of the sequence ($M = 21.79$ ms). Hence, implicit sequence learning by subjects who were aware that target information followed a sequence was similar to that of subjects who were unaware of the sequence. It is noteworthy that a significant number of subjects were not successful in employing an explicit learning mode despite being instructed to do so in the present experiment and that few subjects in Experiment 1a adopted an explicit learning mode. This suggests that the complexity of the search task or of the sequence may have discouraged explicit learning.

This experiment also revealed that the learning of ambiguous sequence associations seems to be benefitted by intention to learn in addition to the availability of attentional resources. This conclusion
is based on the finding that ambiguous associations showed less
evidence of implicit learning than did unique associations, but
seemed to be learned as well as unique associations under explicit
learning conditions. Hence, the learning of ambiguous associations
may require the intentional allocation of available attention to the
learning process.

In addition, the availability of attentional resources seems to
benefit unique and ambiguous-association learning equally when
learning is intentional (see Table 5). This is evidence against the
hypothesis that ambiguous associations require the use of an
attentional learning mechanism that can handle hierarchical
relationships and which is distinct from a nonattentional associative
learning mechanism used to learn structures with unique associations
(e.g., Cohen et al., 1990). Instead, the same learning processes are
most likely used for both types of associations, as others have
suggested (e.g., Cleeremans & McClelland, 1991; Frensch et al.,
1994). However, these processes may not be very effective at
learning ambiguous associations in the absence intentional allocation
of cognitive resources.

**Experiment 1c**

This experiment was conducted to examine implicit sequence
learning when focused attention is used in both the search and target
identification phases of a search task. The demands of focused-
attention search are greater than those of distributed-attention search
because they require the serial processing of individual search
elements. If implicit sequence learning requires attentional
resources, it might be affected adversely by the demands of the search task in this experiment. Implicit sequence learning might also be limited by focused-attention search because distractor stimuli, in addition to the sequenced target stimuli, are processed using focused attention.

Conversely, more sequence learning might occur when focused visual attention is used. In Experiment 1a, focused attention should have been used to process targets in narrow-focus conditions because the unique target color cued attention to the target. If more attentional resources are required by focused attention when it is used to distinguish a target from similar search elements (as in the present experiment) than when it is given to a cued target, the greater amount of attention directed toward the target might increase the implicit learning of target patterns.

Method

Facilities. Research facilities were identical to those of Experiment 1a.

Participants and Design. Participants were 40 male volunteers from the USAF basic training program at LAFB. Five reported color-deficient vision or made at least four color identification errors on a color test. Six reported a left-hand preference for throwing or writing. Eleven reported left-eye dominance. All subjects performed eight 120-trial blocks of the search task. Within-subject factors were block (eight blocks) and set size (six vs. nine search elements). The experiment began at approximately 0730 hrs and lasted approximately 2 hrs. Other details were identical to those
of Experiment 1a.

Search array. Stimuli were the letters I, L, T, and E, oriented 15 deg left, 15 deg right, 75 deg left, or 75 deg right, and presented in white on a black background. Horizontal and vertical lines of the letters were 0.9 and 1.2 cm in length, respectively, with a thickness of 0.3 cm. Letters were displayed in 6 or 9 positions of a centered 3 element x 3 element array surrounded by a 6 x 6 cm box drawn with a 2-mm white line (see Figure 7). In six-stimulus displays, stimuli appeared in two randomly-chosen adjacent rows or columns. Head position was not fixed, but based on a viewing distance of 55 cm, the search array and surrounding box subtended a visual angle of 6.2 deg horizontally and vertically.

![Image of a search array](image)

Figure 7. A display like those in Experiment 1c. The task was to find the unique letter and identify its orientation. The target is in the right position of the center row and the correct response is 15 deg left.
Targets. The first seven blocks of trials were sequenced-orientation blocks, in which the response feature, target orientation, followed the 12-trial sequence followed by the response feature in Experiment 1a (i.e., 3-4-1-2-4-1-2-3-4-1-3-2), and target identity followed the 12-trial sequence that target color followed in Experiment 1a (i.e., 3-1-2-4-1-2-3-1-4-3-2-1). Block 8 was the randomized-orientation block, in which orientation was randomly assigned to targets with the constraint that it was not the same in consecutive trials. Target location was randomly assigned without consecutive repetition.

Distractors. Two of the three letters not used as the target were each assigned to an approximately equal number of randomly-chosen array positions (e.g., three and two positions when the set size was six). Each orientation was assigned to one or two (always two in nine-element arrays) randomly-chosen distractors with the constraint that all distractors with the same identity had different orientations.

Procedure. The procedure was identical to that of Experiment 1a with the exceptions described below. Trials were terminated by a response or else ended after a response period of 4.5 s in the first block of trials, 4.25 s in the second, and 4 s in the remainder. Response periods included the 0.5-s period after the search array was covered by a black mask, in which only the box outline was displayed. Participants searched arrays of six or nine bars for the unique letter (the target) and pressed the key assigned to its orientation. Eight blocks of 120 trials were performed after practice trials. The first seven of these were sequenced-orientation blocks.
After completing the eight blocks of trials, subjects were asked to generate both the target orientation (i.e., the response feature) sequence and the target identity sequence. Subjects did not perform the sequence recognition task.

Results and Discussion

Only 21 subjects met the accuracy rate criterion of 75% or better. The 19 subjects who did not meet this criterion were analyzed separately. The analyses revealed no reliable evidence of sequence learning, however, and will not be discussed further. One subject who, based on generation test performance, appeared to have used an explicit mode of sequence learning was also excluded from analyses. The performance of subjects who were left-handed, left-eye dominant, or who had color-deficient vision did not differ descriptively or statistically from that of the others. Hence, the data of the remaining 20 subjects were analyzed together. Trials were discarded if the RT was 2.5 standard deviations above or below the mean RT for each block of trials performed by each subject or if a response was not made before the response period expired (2.6% of trials), and incorrect trials were excluded from RT analyses (mean PE = 9.5%).

Sequence and Association Learning. Sequence learning was quantified by the mean RT and PE disruptions between Blocks 7 and 8. These disruptions are shown in Table 8 for all associations (in Column 1), unique associations (in Column 2), and ambiguous associations (in Column 3). Mean RTs for all sequence associations and for unique associations are shown across all blocks of trials in
Table 8
**Mean Increases in Reaction Time (in ms) and Percent Errors from Block 7 to Block 8 for Different Types of Sequence Associations in Experiment 1c**

<table>
<thead>
<tr>
<th>Sequence Associations</th>
<th>All</th>
<th>Unique</th>
<th>Ambiguous</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-9.33</td>
<td>179.35</td>
<td>-85.74</td>
</tr>
<tr>
<td></td>
<td>(122.54)</td>
<td>(229.00)</td>
<td>(114.23)</td>
</tr>
<tr>
<td>PE</td>
<td>1.8</td>
<td>3.7</td>
<td>1.5</td>
</tr>
<tr>
<td></td>
<td>(4.6)</td>
<td>(8.0)</td>
<td>(4.2)</td>
</tr>
</tbody>
</table>

*Note.* Standard deviations of reaction time and percent error increases are in parentheses. Negative numbers represent improvements, instead of disruptions.

Sequence generation scores that ranged from 0 to 4 sequence elements correctly recalled in order and only one report of sequence awareness (by a subject excluded from analyses) are evidence that any learning tended to be implicit. In addition, separate repeated measures ANOVAs were performed to assess the effects of block (Block 7 vs. 8) on RTs and PEs for the whole sequence, unique associations, and ambiguous associations. The results of these analyses are given in Appendix G. A main effect of block on RTs for ambiguous associations ($F(1,19) = 11.27, p = .003, \text{MSE} = 6,524$) reflected a decrease in RTs across blocks, rather than a disruption. Hence a main effect of block on RTs for unique associations ($F(1,19) = 12.27, p = .002, \text{MSE} = 26,221$), provided the only RT evidence of
sequence learning. Examination of individual subject RTs for unique associations showed that mean RTs increased between Blocks 7 and 8 for 16 of the 20 subjects. In addition, marginally significant main effects of block on PEs were found for unique associations ($F(1,19) = 4.35, p = .051, MSE = 0.003$) and for all associations ($F(1,19) = 3.20, p = .089, MSE = 0.001$), but not for ambiguous associations. In both cases, the PE rate of 15 subjects increased between blocks.

These analyses reveal learning of unique associations. Further, the mean RT increase for unique associations ($M = 179.35$) was substantial relative to that observed in Experiments 1a and 1b and seems more characteristic of explicit than of implicit learning. In addition, Figure 8 shows that evidence of learning appeared suddenly and late in the experiment (i.e., between Blocks 6 and 7).

Examination of individual subject RTs revealed large decreases in mean RTs ($> 100$ ms) for unique associations between Blocks 6 and 7 in the performance of 14 subjects, indicating that RT performance shown in Figure 8 is representative of most subjects.
Figure 8. Mean reaction time (in ms) as a function of block for all sequence associations and for unique associations during search task performance in Experiment 1c.
Search Task Performance Effects on Sequence Learning.

Subjects were divided into two groups based on their accuracy rates. High accuracy group members had accuracy rates of 92% or less ($M = 0.947$, $SD = 0.03$, $n = 9$). Low accuracy group members had accuracy rates between 75 and 92% ($M = 0.872$, $SD = 0.0613$, $n = 11$). A 10-ms RT disruption was observed in the high accuracy group, whereas there was no evidence of an RT disruption in the low accuracy group. However, ANOVAs performed to compare effects of block (Block 7 vs. 8) in the two accuracy groups (high vs. low) did not reveal effects of accuracy group on either RT or PE disruptions. Possibly, any potential effects of overall accuracy on sequence learning were overwhelmed by other factors, such as task difficulty, which discouraged sequence learning.

In other parts of Experiment 1, trials were timed so that subjects in all conditions performed at the same rate. In this part, however, trials ended either when the subject pressed the response key or when the response period expired. Consequently, it was possible to examine whether the length of time between stimulus presentations affected how well the sequence was learned. Subjects were assigned to the fast-RT group if their mean RT was less than 2250 ms ($M = 2050.18$, $SD = 221.42$, $n = 9$). They were assigned to the slow-RT group if their mean RT was greater than or equal to 2250 ms ($M = 2524.2$, $SD = 274.72$, $n = 11$). There was little redundancy between accuracy and RT performance groupings (e.g., only five high accuracy group members were also in the fast-RT group).

Mean RT and PE disruptions of 5 ms and 2.5% were found for
the fast-RT group, whereas no RT performance disruption occurred in the slow-RT group, which had a mean PE disruption of 1.3%. ANOVAs used to compare effects of block (Block 7 vs. 8) in the two RT groups (fast-RT vs. slow-RT) did not demonstrate any significant effects. However, separate analyses of each RT group revealed an effect of block on the PEs of the fast-RT group \( F(1,8) = 5.69, p = .044, \text{MSE} = .0005 \), but not of the slow-RT group. This suggests that the pacing of response and stimulus events might influence implicit sequence learning.

The small sequence learning advantage for the fast-RT over the slow-RT group supports the hypothesis of Frensch et al. (1994) that the time between stimulus presentations affects the number of stimuli that are held simultaneously in memory and thereby affects sequence learning. In an experiment performed by Frensch et al. (1994) to evaluate this hypothesis, inter-stimulus intervals of approximately 1700 ms impaired, but did not eliminate, sequence learning relative to shorter inter-stimulus intervals. Hence, the failure to detect sequence learning in the main analyses of the present experiment could have been a consequence of slow RTs.

**Search Task Learning.** As can be seen in Figure 8, mean search task RTs decreased across Blocks 1 through 7. Accordingly, there was a main effect of block on RTs \( F(6,114) = 40.44, p = .0001, \text{MSE} = 14,188 \), yielded by a repeated measures ANOVA of block (Blocks 1 through 7). Mean PE decreased from 11 to 8% across these blocks, but this change was not statistically significant.
Set-Size Effects on Search Task Performance. Because focused attention was required to process search task stimuli serially in this experiment, the three additional stimuli when the set size was nine, compared to six, were expected to cause an increase in RTs. An 8 x 2 (Block x Size) repeated-measures ANOVA confirmed this expectation, revealing a main effect of set size on RTs ($F(1,40) = 4.51, p = .04$, $MSE = 707,664$) which reflected a mean difference of 195 ms between set sizes. There was not an effect of set size on PEs and there was not an interaction of set size with block for either RTs or PEs.

Summary of Experiment 1c Results. Results of this experiment indicate that the use of focused attention to perform a search task was detrimental to sequence learning. Only unique sequence associations seemed to be learned and this learning appeared much later in task performance than in the preceding experiments. Because many differences exist between the search task performed in this experiment and the one performed in Experiment 1a, it is impossible to determine what aspects of focused-attention search were most harmful to sequence learning. Differences between the tasks include attentional demands (subjects' comments, high RTs, and low accuracy rates testify to the high demands of the task in this experiment), stimulus-presentation intervals (they were longer in this experiment), and the use of focused attention to process one versus many stimuli in a given trial.

One contribution of this experiment is support the results provide for the hypothesis of Frensch et al. (1994) that sequence
learning may depend partially on the formation of associations between stimuli that are held simultaneously in memory. This support is provided by the demonstration of sequence learning by the fast-RT group only. However, the difference between the performance disruptions of the two RT groups is small and hence, its implications are limited. Furthermore, the difference alternatively could be interpreted as support for an instance-based explanation of implicit learning, whereby implicit learning depends on the joint representation of events and their immediate consequences, or the next event. The sooner the next event occurs, the more likely it is to be included in an instance with the preceding event.

The sudden large decrease in RTs between Blocks 6 and 7 for unique sequence associations suggests that implicit learning might have different characteristics in demanding tasks, such as focused-attention search tasks, compared to less demanding tasks. In demanding tasks, learning might be demonstrated as a leap in task performance levels, caused by a sudden awareness (i.e., explicit knowledge) of implicitly-learned information. In less demanding tasks, it might be demonstrated as a gradual improvement in task performance. In other words, implicit learning that occurs during the performance of demanding tasks might be inaccessible and may be demonstrated only once it becomes explicit. This is consistent with the claim of DeSchepper and Treisman (1996) that retrieval, but not storage, processes may require attention. This is also consistent with the 179-ms RT disruption found for unique associations in the present experiment, the size of which suggests that
knowledge became explicit before it was demonstrated.

Hence, it is hypothesized that implicit learning may not be demonstrated during the performance of very complex tasks until implicitly-learned information becomes explicit. According to this hypothesis, when a sequence or sequence component enters awareness and becomes explicit, then some attentional resources may be pulled from the primary task and allocated to the intentional retrieval and use of implicitly-learned information to guide performance. This hypothesis predicts that implicit learning in demanding tasks will be difficult to assess because learning is not evident until it becomes explicit. Consequently, implicit learning may have been better in the present experiment than was implied by performance. In particular, ambiguous-association learning might have occurred, but was not tapped by the performance-disruption measure.

**Analysis of Visual Attention Strategy.** As in Experiment 1a, S-R compatibility effects were assessed in order to determine if they would provide information about the visual attention strategy used to perform the search task in this experiment. Trials included in the compatibility analyses were those in which targets appeared in the left or right column of the search array and the correct response key was at the left or right end of the response key row. As in Experiment 1a, compatible trials were those in which the target was in the left column and the correct response key was on the left, and vice versa, and incompatible trials were those in which the correct response key was opposite the side on which the target appeared.
Compatibility effects were assessed by comparing the RTs and PEs of compatible and incompatible trials.

Blocks 1 though 7 and Block 8, in which target orientation followed a random pattern, were submitted to separate repeated measures ANOVAs to examine the effects of compatibility (compatible vs. incompatible). These revealed a marginally significant main effect of compatibility on RTs in Blocks 1 through 7 ($F(1,19) = 3.25, p = .087, \text{MSE} = 3,093$). Compatibility did not affect PEs, and in Block 8, a significant effect of compatibility on RTs was not in the expected direction ($F(1,19) = 5.33, p = .032, \text{MSE} = 27,870$). Incompatible trial RTs were, on average, 122 ms faster than compatible trial RTs in Block 8. There is not an obvious explanation of this negative compatibility effect in Block 8.

**Experiment 1d**

Sequence learning observed in the previous experiments was less than what is usually seen in the literature. The purpose of this experiment was to measure implicit learning of a sequence in the orientations of stimuli during performance of a serial RT task. Sequence learning observed in this experiment would indicate the extent to which implicit sequence learning in preceding experiments was adversely affected by task complexity.

**Method**

**Facilities.** Research facilities were identical to those of Experiment 1a.

**Participants and Design.** Participants were 21 male volunteers from the USAF basic training program at LAFB. One subject
reported color-deficient vision. Three reported a left-hand preference for throwing or writing. Seven reported left-eye dominance. All subjects performed four 120-trial blocks of the serial RT task, hence, block was treated as a within-subjects factor. The experiment began at approximately 0730 hrs and lasted approximately 0.75 hrs. Other details were the same as in Experiment 1a.

**Stimuli.** Stimuli were the bars used in Experiment 1a, centrally-displayed, one at a time. Stimulus orientation and color followed the same sequences as in the narrow-focus condition of Experiment 1a.

**Procedure.** The procedure of Experiment 1a was followed in this experiment, except that only a single bar was displayed centrally in each trial and participants pressed the key assigned to its orientation. Also, only four blocks of trials were performed after the practice trials. Blocks 1 - 3 were sequenced-orientation blocks. After completing all four blocks of trials, participants were asked to generate the target orientation and then the color sequence. They did not perform the sequence recognition test.

**Results and Discussion**

Seven subjects designated as explicit learners based on their generation scores and reports of sequence awareness were excluded from the analyses reported below. Performance by the subject with color-deficient vision was similar to that of the other subjects, but that subject was excluded because he was an explicit learner. Likewise, the performance of the left-handed and left-eye dominant subjects did not differ from that of the other subjects. Thus, the data
of 14 subjects were submitted to the analyses below. Trials were
discarded if the RT was less than 150 ms or if a response was not
made before the response period expired (1.3% of trials), and
incorrect trials were excluded from RT analyses (mean PE = 3.2%).

**Sequence Learning.** Sequence learning was quantified by the
mean disruptions in RTs and PEs between Blocks 3 and 4. These
disruptions were 24 ms (SD = 64.82) and 1.1% (SD = 3.42),
respectively, and are similar in magnitude to performance
disruptions observed in the preceding experiments. Data were first
submitted to repeated-measures ANOVAs of block (Block 3 vs. 4) to
assess sequence learning. These did not reveal any significant
effects. The results are given in Appendix H.

**The Effects of Search Task Accuracy on Sequence Learning.**
Data were next submitted to mixed-design ANOVAs with the factors
block (Block 3 vs. 4) and accuracy group (high vs. low). Subjects
with overall accuracy rates of 97% or better (M = 0.982, SD = 0.02,
N = 8) were in the high accuracy group; subjects with overall
accuracy rates that were less than 97% (M = 0.958, SD = 0.027, N =
6) were in the low accuracy group. No main effects of accuracy
group or block were found. However, there was a Block x Accuracy
Group interaction for RT (F(1,12) = 12.62, p = .004, MSE = 1,109),
caused by an effect of block on RTs in the high accuracy group
(F(1,7) = 24.63, p = .002, MSE = 632), but not in the low accuracy
group. The mean RT increase in the high accuracy group was 62
ms. In contrast, RT performance was not disrupted in the low
accuracy group. The changes in mean RT between Blocks 3 and 4
Figure 9. Mean reaction time (in ms) as a function of block for low and high accuracy groups of subjects in Experiment 1d.
for each of the accuracy groups, in addition to the mean RTs of each group across blocks, can be seen in Figure 9. Although no effects on PEs were found in the main analysis, an effect of block on PEs in the high accuracy group provided additional evidence of sequence learning by that group ($F(1,7) = 6.44$, $p = .039$, $MSE = 0.0002$). An examination of individual subject RTs revealed that all eight subjects in the high accuracy group and only three of the six subjects in the low accuracy group showed increased RTs between Blocks 3 and 4.

**Search Task Learning.** To assess search task performance across blocks of trials, RTs and PEs in the first three blocks of the serial RT task were analyzed using a repeated measures ANOVA. These revealed a main effect of block on RTs ($F(1,12) = 6.22$, $p = .013$, $MSE = 1,840$), which can be seen in Figure 9 as a decrease in the mean RTs of both high and low accuracy groups across blocks. There was not an effect of block on PEs, which were approximately 3%, on average, in each of the three blocks.

**Summary of Experiment 1d Results.** This experiment demonstrated mean RT and PE disruptions that were similar in size to those found for implicit learners in Experiments 1a and 1b. This suggests that implicit sequence learning in those experiments was not adversely affected by the complexity of the search task, relative to a simpler (i.e., serial RT) task.

In addition, the effect of performance accuracy on RT disruptions in this experiment was dramatic. A mean disruption of 62 ms was observed for the group of eight high-accuracy subjects, compared to no disruption for the group of six low-accuracy
subjects. In contrast to this relatively large difference in mean RT
disruption, the mean accuracy rates of the groups differed by the
small amount of approximately 2.5% (and standard deviations were
similar). Most surprising is that the low accuracy group did not
demonstrate sequence learning, considering that the mean accuracy
rate was relatively high (96%).

Experiment 2

The sequence used in Experiment 1 was followed by the response
feature of the target stimulus and hence, by responses as well.
However, in some complex tasks, stimuli are patterned but responses
are not. Implicit learning of patterns in perceptual encoding
operations (i.e., in stimuli) has not been conclusively demonstrated.
In particular, studies that seem to have shown implicit learning of
perceptual operations (e.g., Fendrich et al., 1991; Howard et al.,
1992) often fail to rule out a response-selection locus of learning.
Hence, in the present experiment, implicit learning of a sequence
followed by a stimulus feature that was not assigned to responses was
examined. As in Experiment 1, implicit learning was examined in
the context of a time-pressured search task with either focused or
distributed attentional requirements. Search arrays consisted of 16
bars and were similar to those used in Experiment 1 (see Figure 10).
The task was to find a uniquely-colored bar (the target) using a
parallel, distributed-attention search strategy, and to identify its
location.

For two-thirds of participants, response keys were each assigned
to a position within quadrants, such that one key was assigned to the
upper-left position of each quadrant, another was assigned to the upper-right position of each quadrant, and so on. Half of these participants were in the narrow-focus condition and half were in the narrow-focus control condition. Visual attention was expected to be focused on the specific location of the target in these conditions. In contrast, the third of subjects assigned to wide-focus conditions identified the quadrant in which the target appeared. Identification of the target quadrant can be achieved using a wide spotlight of attention (one that encompasses the quadrant) and hence, these subjects should have been able to perform the task using distributed visual attention. Target color followed a 12-trial sequence in each condition. In the control condition, target location (and therefore responses) also followed the sequence.

If sequence learning is observed in the narrow-focus and wide-focus conditions, this would be evidence that patterns in perceptual encoding operations, and not just in response selection operations, can be learned implicitly. Furthermore, if sequence learning in these two conditions is similar, this could mean that stimuli were similarly represented, despite different perceptual requirements. In this case, series of symbolic or verbal representations of the stimuli may have been learned, rather than series of spatial images.

**Method**

**Facilities.** The research facilities were identical to those used in Experiment 1.

**Participants and Design.** The participants were 58 male and 18 female volunteers from the USAF basic training program at LAFB.
Color-deficient vision was reported or detected in five. Seven reported a left-hand preference for throwing or writing. Left-eye dominance was reported by twenty. Subjects were randomly assigned to one of three between-subjects conditions (narrow-focus, wide-focus, and narrow-focus control). All subjects performed six blocks of 120 trials, hence, block was considered a within-subject factor. Additional details were the same as in Experiment 1.

Search array. Search arrays were identical to those used in the narrow-focus condition of Experiment 1, except that the array size was always 16, and the array was divided into quadrants by two 1-mm black lines (see Figure 10).

![Search array diagram]

**Figure 10.** A display like those in Experiment 2. **Note.** The shades of the bars represent colors.
Targets. In sequenced-feature blocks, target color followed the 12-trial sequence that target orientation followed in Experiment 1 and target orientation followed the 12-trial sequence that target color (or identity) followed in Experiment 1. In the narrow-focus control condition, target location, the response feature, followed the same sequence as color (i.e., 3-1-2-4-1-2-3-1-4-3-2-1, where the elements 1, 2, 3, and 4 represented the upper left, upper right, lower left, and lower right corners of all quadrants, respectively). In randomized-feature blocks, target color, orientation, and location were chosen randomly, with the constraint that they were not the same in consecutive trials.

Distractors. The four possible orientations were randomly assigned to the distractors, with the constraint that each was used approximately equally in each display (i.e., for either three or four distractors). Colors not assigned to the target were randomly assigned to the distractors with the constraints that each color was used equally often and the same color was assigned to all of the distractors in the target quadrant.

Procedure. The procedure was identical to that of Experiment 1 except for the differences that follow. Trials were terminated by a response or else ended after response periods of 2.5 s in the first block of trials, 2.25 s in the second, and 2 s in the remainder. Response periods included the 0.5-s period after the search array was covered by a black mask, in which only the box outline was displayed. The target locations upper left, upper right, lower left, and lower right were mapped from left to right to response keys.
Participants searched arrays of 16 bars for the uniquely-colored target and pressed the key assigned to its location. In the wide-focus condition, response keys were assigned to quadrants. In narrow-focus and narrow-focus control conditions, response keys were assigned to the four stimulus positions within each quadrant. Six blocks of 120 trials were performed. In sequenced-feature blocks (i.e., Blocks 1 - 5), target color and orientation followed 12-trial sequences. In addition, target location followed the same sequence as target color in the narrow-focus control condition.

After completing the six blocks of trials, subjects were asked to generate the color sequence by typing the first letter of the color names, and then to generate the orientation sequence using the response keys. Next, participants performed 24 color-sequence recognition test trials and 24 orientation-sequence recognition test trials. Half of each set of trials consisted of the 12 four-trial subsequences derived from the sequence and half consisted of new subsequences with fewer structural constraints. The two types of trials were intermixed and displayed in a different random order for each subject. The order in which the tests were performed was counterbalanced across subjects.

Results and Discussion

Sixty-nine participants met the accuracy rate criterion of 75% or better. Five were classified as explicit learners (all were in the narrow-focus control condition) on the basis of their generation scores, recognition scores, and reports of awareness, and were excluded from analyses. The performance of color-deficient, left-
handed, and left-eye dominant subjects did not differ statistically from that of the others. However, the RT disruption between Blocks 5 and 6 differed for males and females, with a 14-ms mean disruption for females and no disruption for males ($F(2,58) = 5.68$, $p = .021$, MSE = 826). Females were balanced across conditions (four or five were in each), but approximately half as many males were in Condition 3, compared to the numbers in Conditions 1 and 2. More sequence learning occurred in Condition 3 than in the other two conditions, as described below, hence, the small proportion of males in this condition probably caused the gender difference. Analyses reported below include the data from all 64 subjects classified as implicit learners. Trials were discarded if the RT was 2.5 standard deviations above or below the mean RT for each block of trials performed by each subject or if a response was not made before the response period expired (4.9% of trials), and incorrect trials were excluded from RT analyses (mean PE = 7.4%).

**Sequence and Association Learning.** Sequence learning was quantified by the mean RT and PE disruptions between Blocks 5 and 6. Disruptions were not observed in the narrow-focus and wide-focus conditions, indicating that no sequence learning occurred in these conditions. Mean changes in RTs and PEs between Blocks 5 and 6 are shown in Tables 9 and 10, respectively for all sequence associations and for unique associations. Figure 11 shows mean RTs for unique associations across all blocks in each of the between-subjects conditions.
Table 9
Mean Increases in Reaction Time (in ms) from Block 5 to Block 6 for Different Types of Sequence Associations in Experiment 2

<table>
<thead>
<tr>
<th>Condition</th>
<th>Sequence Associations</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Unique</td>
<td></td>
</tr>
<tr>
<td>Wide-Focus</td>
<td>-14.45</td>
<td>4.42</td>
<td>(58.32)</td>
</tr>
<tr>
<td>n = 25</td>
<td>(45.90)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Narrow-Focus</td>
<td>-19.59</td>
<td>-34.09</td>
<td>(58.32)</td>
</tr>
<tr>
<td>n = 23</td>
<td>(38.10)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Narrow-Focus Control</td>
<td>8.74</td>
<td>47.22</td>
<td>(73.39)</td>
</tr>
<tr>
<td>n = 16</td>
<td>(40.60)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Standard deviations of reaction time increases are in parentheses. Negative numbers represent improvements, instead of disruptions.

ANOVA were performed on RTs and PEs to examine performance disruptions, or lack thereof, in the different conditions. These revealed a main effect of condition on both RTs ($F(2,61) = 17.43, p = .0001, \text{MSE} = 19.208$) and PEs ($F(2,61) = 4.64, p = .013, \text{MSE} = 0.0031$) indicated that performance was better in the wide-focus condition than in the other two conditions. In addition, a marginally significant effect of block on PEs reflected not a disruption, but a decrease, in PEs from Block 5 to Block 6 ($F(1,61) = 3.63, p = .061, \text{MSE} = 0.0006$). There was not an effect of block on RTs. Hence, this analysis did not reveal any evidence of sequence learning.
Figure 11. Mean reaction time (in ms) as a function of block for unique associations in each between-subject condition of Experiment 2.
Table 10
Mean Increases in Percent Errors from Block 5 to Block 6 for Different Types of Sequence Associations in Experiment 2

<table>
<thead>
<tr>
<th>Condition</th>
<th>Sequence Associations</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Unique</td>
<td></td>
</tr>
<tr>
<td>Wide-Focus</td>
<td>-0.8</td>
<td>-4.2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.7)</td>
<td>(7.1)</td>
<td></td>
</tr>
<tr>
<td>Narrow-Focus</td>
<td>-1.2</td>
<td>-3.8</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.5)</td>
<td>(5.6)</td>
<td></td>
</tr>
<tr>
<td>Narrow-Focus Control</td>
<td>-0.66</td>
<td>1.8</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.4)</td>
<td>(7.6)</td>
<td></td>
</tr>
</tbody>
</table>

Note. Standard deviations of percent error increases are in parentheses. Negative numbers represent improvements, instead of disruptions.

However, an ANOVA performed on unique associations yielded a main effect of block on PEs (F(1,61) = 5.84, p = .019, MSE = 0.002) and a Block x Condition interaction for PE (F(2,61) = 4.61, p = .014, MSE = 0.002). For RT, there was a main effect of condition (F(2,61) = 11.13, p = .0001, MSE = 21,210), that was mediated by an interaction with block (F(1,61) = 6.74, p = .002, MSE = 2,329). The Block x Condition interactions for PE and RT reflected the fact that whereas RTs were disrupted (p = .021) and PEs were not reduced in the narrow-focus control condition, there was a trend of improvement across blocks in the other two conditions. Specifically, RTs and PEs were reduced in the narrow-focus condition (both p's < .04) and PEs were reduced (p = .002) while RTs were unchanged in the wide-focus condition. Thus, these analyses demonstrate unique-
association learning only in the condition in which the sequence was followed by both the response feature (target location) and the feature used to find the target (target color). This can be seen in Figure 11, which depicts mean RTs for unique associations across blocks of trials. In addition, results of the main analyses of all association and of unique associations are given in Appendix I.

Search Task Learning. To examine the changes in RTs and PEs across Blocks 1 through 5 in the three between-subject conditions, ANOVAs were performed with the factors block (Blocks 1 through 5) and condition (wide-focus, narrow-focus, and narrow-focus control). Main effects of condition on RTs ($F(2,61) = 15.63, p = .0001, \text{MSE} = 60,398$) and PEs ($F(2,61) = 6.31, p = .003, \text{MSE} = 0.008$) reflected better performance in the wide-focus condition. Mean RT and PE in that condition were 879 ms and 5%, respectively, whereas mean RTs were 1042 ms and 1022 ms, and mean PEs were 8% and 9% in the narrow-focus and narrow-focus control conditions, respectively. Main effects of block on RTs ($F(4,244) = 168.89, p = .0001, \text{MSE} = 3,168$) and PEs ($F(4,244) = 2.92, p = .043, \text{MSE} = 0.002$) indicated that performance improved across blocks in all conditions.

Because sequence differences among the three conditions were only found for unique associations, RTs and PEs for unique associations in Blocks 1 through 5 also were submitted to ANOVAs of block and condition. These yielded main effects of condition ($F(2,61) = 15.12, p = .0001, \text{MSE} = 60,776$) and block ($F(4,244) = 109.67, p = .0001, \text{MSE} = 5,492$) on RTs, in addition to a marginally
significant Block x Condition interaction ($F(8,244) = 2.11, p = .06, \text{MSE} = 5.942$). This interaction probably represents the steeper decrease in mean RTs in the narrow-focus and narrow-focus control conditions, relative to the wide-focus condition. No effects on PEs were found for unique associations.

**Summary of Experiment 2 Results.** The absence of disruptions in performance in the wide-focus and narrow-focus conditions of this experiment suggests that implicit sequence learning only will occur when sequenced stimulus features are assigned to responses, and that relevance of the stimulus features to task performance is not sufficient. These results therefore indicate that perceptual encoding processes are not learned implicitly (or that learning them does not benefit performance), and support the hypothesis that when sequence learning occurs, it involves the learning of series of S-R mappings.

However, other results of this experiment indicate that implicit learning may be restricted to unique associations between S-R mappings. This experiment demonstrated unique-association learning, but not ambiguous-association learning. These and similar results found in Experiment 1c are suggestive of a dissociation between unique and ambiguous associations. Based on the improvement in ambiguous-association learning when learning was explicit in Experiment 1b compared to when it was implicit in the other experiments, this dissociation might be related to intention to learn. Specifically, ambiguous-association learning might occur only if attention is intentionally allocated to learning. For attention to be intentionally allocated to sequence learning, the sequence first must
be detected. Hence, if subjects failed to detect the sequential patterns in this experiment, they might not have implicitly learned ambiguous associations. According to this explanation of the observed impairment in ambiguous-association learning, workload manipulations that affect the amount of available attention will affect ambiguous-association learning only under conditions of intentional learning. This explanation is consistent with the results of the present experiment if the assignment of four stimulus locations, albeit with the same response codes (e.g., upper left), to each response in the narrow-focus control condition, prevented sequence detection and awareness. It is also consistent with the results of Experiment 1c if high task demands in that experiment made sequence detection unlikely.

The suggestion above that S-R assignments may have inhibited ambiguous-association learning conflicts with the hypothesis that a single response code can represent multiple stimuli as effectively as a single stimulus. This could mean that despite the irrelevance of target quadrants to responses in the narrow-focus control condition, the quadrant in which a target appeared may have been tagged or somehow represented so that the location sequence was not just of relative target locations, but was of relative locations in specific quadrants. The specific target quadrants did not follow the repeating location sequence and hence, such information would have obscured the sequence of relative positions, reducing the likelihood that the sequence would be detected.
General Discussion

The present research investigated aspects of implicit learning that are relevant to its role in complex task performance. Major results include the finding that implicit sequence learning in the performance of a distributed-attention search task (Experiment 1a) was similar to implicit sequence learning in performance of a simpler serial RT task (Experiment 1d). Furthermore, implicit learning during search task performance was unaffected by the performance of a secondary letter-set rehearsal task (Experiment 1a) or by whether task instructions encouraged the use of focused or distributed visual attention to process targets. However, implicit learning was affected by sequence structure. In particular, it appeared that ambiguous associations did not tend to be learned implicitly. In addition, implicit learning did not occur when sequenced stimuli were not assigned to responses (Experiment 2). Hence, implicit learning of unique associations between S-R pairings was demonstrated during the performance of a task considered to be relatively complex, under dual-task workload conditions, and under different perceptual requirements. Furthermore, although explicit sequence learning was found to be superior to implicit sequence learning, this difference was greatly diminished under dual-task conditions, which adversely affected explicit sequence learning (Experiment 1b).

Limits of Implicit Learning

The present results indicate that implicit learning can benefit performance in complex tasks. However, they also reveal that the
contributions of implicit learning to performance may be limited. Measures of sequence learning in terms of performance disruptions when transferred to a random stimulus presentation were small in this research, compared to those typically found in sequence learning studies. This was true even in Experiment 1d, which featured the traditional serial RT task. This difference is caused partly by the frequent inclusion of explicit learners in analyses of sequence learning by other researchers, however, even the mean RT disruptions of subjects classified as "less aware," based on explicit knowledge test scores, have tended to range between 60 and 150 ms for hybrid sequences learned under single-task workload conditions (e.g., Curran & Keele, 1992; Stadler, 1989; Willingham et al., 1989). In comparison, the mean RT disruptions observed in the present experiments ranged from 0 to 32 ms under single-task conditions. Numerous factors that might have restricted implicit sequence learning in these experiments can be identified. These factors include accuracy rate, response code complexity, the time duration between sequenced events, sequence structure complexity, the resource demands of task performance, and whether sequenced stimuli were assigned to responses.

Effects of Accuracy Rate on Sequence Learning

Experiments 1a, 1b, and 1d demonstrated that higher accuracy rates tended to be associated with greater sequence learning. This association suggests that the correct selection and/or execution of responses is important to both implicit and explicit sequence learning. This is consistent with considerations of the importance of
response selection in skill acquisition (e.g., Fendrich et al., 1991) and the hypothesis that sequence learning involves learning series of S-R assignments (e.g., Willingham et al., 1989).

However, rather than interpreting accuracy rate as influencing sequence learning because of the importance of correct response selection, the high accuracy rate might be simply a consequence of learning. According to this interpretation, sequence learning differences might influence accuracy rate. Similarly, sequence learning differences might be produced by a factor which also affects accuracy. Such a factor might be performance motivation. As another example, both accuracy rate and sequence learning improvements could be caused by the acquisition of explicit knowledge.

The acquisition of explicit sequence knowledge would permit subjects to anticipate responses and thereby improve accuracy. Furthermore, explicit sequence knowledge would contribute to the performance disruption observed when the feature sequence was replaced by random presentations. This explanation does not seem to account for the accuracy rate effects observed in this research, however. In particular, comparison of the generation and recognition test scores of the high and low accuracy groups in Experiments 1a and 1b did not reveal any differences, indicating that explicit knowledge is similar in the different accuracy groups.

Whereas accuracy rate might be predictive of sequence learning differences among participants in the present research, it does not seem to account for the relatively small amount of sequence learning
observed across experiments. The mean accuracy rate in most sequence learning studies is high (> 95%), but not higher than those of the high accuracy groups in the present research, for which mean RT disruptions were still smaller than those typically observed (e.g., 32 ms in the narrow-focus condition of Experiment 1a and 62 ms in Experiment 1d). Thus, although overall accuracy could have contributed to the small size of the RT disruptions, other factors, such as response code complexity, the amount of time between stimulus presentations, and sequence structure complexity probably are involved, as well.

Effects of Response Code Complexity on Sequence Learning

Response code complexity might have limited sequence learning in this research. Spatially compatible responses are most often assigned to stimulus locations in sequence learning studies, but response keys were assigned to orientations in the present study. Orientation might be represented by a cumbersome response code (e.g., 75 deg left or small tilt to left), and if sequence learning involves learning either series of stimulus codes or series of stimulus-response mappings, then these more complicated codes could reduce sequence learning efficiency.

Effects of Event Intervals on Sequence Learning

Long trial times also might have contributed to the generally low implicit learning measurements. As Frensch et al. (1994) proposed, time between stimulus presentations might affect the number of stimuli that are held in short term memory simultaneously, and thereby affect implicit learning of associations between stimuli. This
is supported by a small sequence learning advantage for the fast-RT group, compared to the slow-RT group in Experiment 1c.

Mean trial times of less than 1 s are typical of implicit sequence learning studies. These times are much shorter than in the present research, in which trial times were 2 s in Experiments 1a, 1b, and 1d, approximately 2 to 4 s in Experiment 1c, and approximately 1.2 to 2 s in Experiment 2. Consequently, it is feasible that longer trial times interfered with sequence learning in this research. Frensch et al. (1994) found evidence of implicit sequence learning when trial times were approximately 1.7 s, but unfortunately they did not report mean performance disruptions for these data with explicit learners excluded.

**Effects of Sequence Structure Complexity on Sequence Learning**

The 12-trial hybrid sequences used in this research primarily consisted of ambiguous associations. Ambiguous associations did not tend to be learned as well as unique associations, and because they accounted for 75% of sequence associations, they influenced the mean RT disruption measure more than unique associations did. If the proportion of unique associations had been higher, larger RT disruptions probably would have been observed. Hence, the ambiguous sequence associations may have contributed to the relatively low measures of sequence learning in this research.

**Effects of Intention on Learning Different Types of Sequence Associations**

The results of this research also suggest that unique associations are more likely to be learned implicitly than ambiguous associations.
in the absence of awareness. Unique, but not ambiguous, associations were learned in both Experiments 1c and 2. Differences in the attentional requirements of unique and ambiguous-association learning cannot fully account for this finding because both were unaffected by dual-task workload conditions in Experiments 1a and were equally affected by dual-task conditions in Experiment 1b. An alternative explanation of these results, which was discussed previously, is that both attentional resources and the intention to learn are required for ambiguous associations to be learned. According to this explanation, ambiguous associations cannot be learned implicitly unless attention is first intentionally allocated to them. Hence, ambiguous-association learning may not have occurred in Experiments 1c and 2 because search task demands in the former, and S-R assignment or sequence complexity in the latter, prevented sequence detection, and without awareness of the sequence, intentional learning was not possible.

A dissociation between the attentional requirements of ambiguous and unique-association learning was first described by Cohen et al. (1990). They found that ambiguous associations were not learned during performance of a secondary tone-counting task which they classified as "difficult" based on the number of high tones to be counted. Cohen et al. attributed the dissociation to separate learning mechanisms, one that required attentional resources and could learn hierarchical relations and an associative learning mechanism that did not utilize attentional resources. Subsequent studies, however, demonstrated ambiguous-association learning under dual-task
conditions (the secondary tone-counting tasks may have been less difficult in these studies), and the idea of separate learning mechanisms was dismissed (e.g., Cleeremans & McClelland, 1991; Frensch et al., 1994).

The present research revives the hypothesis of Cohen et al. (1990), that unique and ambiguous associations have different attentional requirements. However, it also adds a new twist, specifically that attentional allocation requirements, but not attentional resource requirements, differ. That is, the learning of ambiguous associations, but not of unique associations, appears to require the intentional allocation of attentional resources to learning. The importance of intention is suggested by the absence of ambiguous-association learning in Experiments 1c and 2, and by the dissociation of explicit learning effects in Experiment 1b (ambiguous associations were benefitted more than unique associations by explicit learning, relative to implicit learning). Further evidence is the absence of a dissociation between the learning of unique and ambiguous associations when available attention was varied by a workload manipulation within Experiments 1a and 1b. In studies that have revealed a dissociation of dual-task performance effects on the learning of unique and ambiguous associations (e.g., Cohen et al., 1990), more subjects in single-task than in dual-task conditions may have become aware of the embedded sequence and switched to an intentional, or explicit, learning mode. This imbalance could result in more ambiguous-association learning under single-task than dual-task conditions.
Effects of Performance Demands on Sequence Learning

Sequence learning (i.e., unique-association learning) appeared to occur suddenly and late in Experiment 1c. In contrast, sequence learning appeared to be gradual in the other experiments. One explanation of this difference is that sequence information may have been learned implicitly in Experiment 1c, but the high attentional demands of the focused-attention search task may have prevented the retrieval and use of that implicitly-learned information during early phases of the experiment. This interpretation is partially supported by the finding of DeSchepper and Treisman (1996) that retrieval, but not encoding, processes may require attention. Sequence learning may have finally influenced task performance when the implicitly-learned information became explicit and some of the attentional resources used to perform the search task were reallocated to the retrieval and use of that information.

Implicit Sequence Learning Loci and Mechanisms

Evidence of sequence learning was not detected in the Experiment 2 conditions in which the sequenced feature was not assigned to responses. This indicates that associations between S-R mappings were probably learned in the control condition of that experiment and in Experiment 1. More generally, it may indicate either that sequence learning is confined to response-selection processes or that patterns in perceptual information only can be learned implicitly if they contribute to the selection of an action. This also is consistent with Mayr's (1996) finding of implicit learning of a stimulus location sequence that was not also present in
keypress responses, if the shifting of visual attention to stimulus locations is considered to be a response. In addition, the finding that perceptual requirements (i.e., the allocation of distributed versus focused visual attention to targets) did not affect sequence learning in Experiment 1 suggests that stimuli were represented either verbally or symbolically, and not spatially, in the response-selection stage.

The integral role of responses in implicit sequence learning supports an instance-based model, according to which implicit sequence learning benefits reflect the storage and subsequent activation (i.e., retrieval) of instances that contain response-relevant stimulus information, responses, and the next event or other immediate consequences (e.g., Zießler, 1994). According to this model, a disruption in stimuli, responses, or their co-occurrence might prevent access to next-event information and thereby suppress implicit learning benefits. This model also predicts that a visual attention strategy will only affect implicit learning if it changes. A change in strategy might result in the mismatch of information stored in past instances and retrieval cues perceived using the new strategy.

As an alternative to this particular model, instances that contribute to implicit learning might contain S-R mappings, but not next-event information. In this case, the learning of associations between S-R mappings might be due to a mechanism like that proposed by Frensch et al. (1994), according to which implicit sequence learning depends on the simultaneous storage of S-R instances.
According to either model, implicit sequence learning should not be affected by the performance of secondary tasks that utilize working memory resources, as was observed. Because implicit learning is unintentional, it is unlikely that the storage of S-R instances involves active maintenance in the articulatory loop of working memory, described by Baddeley (1992) as a working memory subsystem used to maintain verbal information in phonological form. Nor is it likely to depend on the visuo-spatial sketchpad of working memory, a subsystem which, according to Baddeley (1992), holds short term visual images and spatial information. Furthermore, if instances already contain next-event information, there is no need for an association-forming process during memory storage. In contrast, the intentional (i.e., explicit) learning of series of instances might require use of the articulatory loop to maintain multiple instances while associations between them are learned. Consequently, it should be affected by performance of a secondary rehearsal task, as was found to be the case. Secondary tasks that interrupt the flow, or structure, of sequenced information, however, appear to interfere with both implicit and explicit learning (e.g., Stadler, 1995), as demonstrated by research that used secondary tone-counting tasks (e.g., Cohen et al., 1990). Such tasks might also impair learning by interfering with instance storage or retrieval.

**Potential Applications**

Once implicit learning is better understood, its role in the performance of complex tasks may be expanded and it may be
utilized to benefit performance in complex tasks and operational environments. For example, training programs could utilize a strategic mix of explicit and implicit learning modes, and display instruments could be configured in a way that encourages the implicit learning of relevant (versus misleading) regularities in displayed information.

The present research demonstrated that unique associations can be implicitly learned and that such learning can improve relatively complex task performance -- as long as sequenced stimulus information is assigned to responses. This research also showed that implicit learning can occur under a variety of perceptual attention conditions and is unaffected by performance of a secondary working memory task. Although it has not been directly examined, implicit learning probably is resistant to the effects of multiple-task performance, as well, as long as none of the tasks interrupts the structure of the information to be learned. In addition, because secondary task performance was found to interfere with explicit sequence learning, the value of implicit learning relative to explicit learning may be especially high in multiple-task environments.

This research reveals potential limits of implicit learning, as well. These limits may influence the role of implicit learning in various task environments, but none should prevent its occurrence. An unexpected limit was that ambiguous associations between serial events do not seem to be implicitly learned. In other words, an association between two consecutive events is unlikely to be learned implicitly if the second event is not uniquely predicted by the first,
and instead is predicted by a combination of two or more preceding events. This is a serious limitation; however, implicit learning still can serve as a means for learning important information. For example, it may be especially useful for learning simple associations that are obscured by a busy task environment or for learning associations that are not easily learned using instruction or hypothesis testing, such as appropriate responses to auditory patterns that are difficult to describe verbally.

**Future Directions**

Additional research is needed to help understand and define the role of implicit learning in complex and operational environments. Research that might be particularly enlightening includes studies that examine implicit sequence learning in highly demanding tasks, the implicit learning of different types and formats of information in complex task settings, and implicit learning contributions to time-pressured decision making.

Implicit learning during the performance of highly demanding tasks might have different characteristics than those observed during the performance of less demanding tasks. The results of Experiment 1c suggest that implicit learning benefits appear suddenly and relatively late in the performance of a very demanding task, rather than in the form of a gradual improvement. Based on the results of this experiment, implicit learning may occur during the performance of such a task, but the learned information may not be retrievable or usable until attention is intentionally allocated to it, as when the implicitly-learned pattern becomes explicit knowledge. Further
investigation would reveal if this is an accurate characterization of implicit learning during the performance of highly demanding tasks and by doing so, would extend current understanding of the capabilities and limits of implicit learning. In addition, implicit learning should be compared to explicit learning under higher workloads that those used in the present research. This research indicates that the advantage of explicit over implicit learning may continue to diminish as the workload increases.

Implicit learning of information other than sequential feature patterns also should be studied in the context of complex task performance. This is essential to determining what operational tasks can be benefitted most by implicit learning and which specific task components can be learned implicitly. As discussed in the introduction, two other paradigms, in addition to the sequence learning paradigm, are commonly used to study implicit learning. The grammar learning paradigm has been used to assess the implicit learning of visual and auditory letter patterns and hence, might be used to study implicit learning of stimulus patterns in complex task settings. The control of dynamic systems paradigm has been used to study the learning of simple and ambiguous if-then rules used to control the state of an artificial system. This paradigm could be used to explore the implicit learning of information presented in different formats (e.g., spatial, verbal, and auditory) and of different levels of complexity (e.g., the number of relevant variables could be manipulated). Furthermore, this paradigm involves decision making and so could be used to study whether implicitly-learned information
is used more effectively than explicitly-learned information in time-
pressured decision making.

Future research might also explore implicit learning in terms of
instance-based models, as some have done already (e.g., Dienes &
Fahey, 1995; Shanks & St. John, 1994; Zießler, 1994). In addition
to investigating whether such a model is capable of accounting for
implicit learning phenomena, specific questions to be explored
include whether instances contain next-event information and
whether a change in visual attention strategy would disrupt sequence
learning benefits by impairing instance retrieval processes.
References


Appendix A

Experiment 1a: Analysis of Variance Summary Table for Sequence Learning Under Different Workload and Perceptual Requirement Conditions

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>RT</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Between subjects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workload (W)</td>
<td>1</td>
<td>2.78*</td>
<td>0.16</td>
</tr>
<tr>
<td>Perceptual Requirement (P)</td>
<td>1</td>
<td>89.84**</td>
<td>36.45**</td>
</tr>
<tr>
<td>W x P</td>
<td>1</td>
<td>2.32</td>
<td>0.00</td>
</tr>
<tr>
<td>S within-group error</td>
<td>111</td>
<td>(22,617.10)</td>
<td>(0.005)</td>
</tr>
<tr>
<td><strong>Within subjects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block (B)</td>
<td>1</td>
<td>32.03**</td>
<td>7.36**</td>
</tr>
<tr>
<td>B x W</td>
<td>1</td>
<td>0.03</td>
<td>0.13</td>
</tr>
<tr>
<td>B x P</td>
<td>1</td>
<td>1.01</td>
<td>0.11</td>
</tr>
<tr>
<td>B x W x P</td>
<td>1</td>
<td>0.00</td>
<td>0.69</td>
</tr>
<tr>
<td>B x S within-group error</td>
<td>111</td>
<td>(1,266.43)</td>
<td>(0.001)</td>
</tr>
</tbody>
</table>

Note. Mean square errors are in parentheses. S = subjects.

*p < .10.   *p < .05.   **p < .01.
Appendix B

Experiment 1a: Analysis of Variance Summary Table for
Unique-Association Learning Under Different Workload and
Perceptual Requirement Conditions

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>RT</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workload (W)</td>
<td>1</td>
<td>3.11*</td>
<td>0.90</td>
</tr>
<tr>
<td>Perceptual Requirement (P)</td>
<td>1</td>
<td>70.42**</td>
<td>29.31**</td>
</tr>
<tr>
<td>W x P</td>
<td>1</td>
<td>2.91*</td>
<td>0.25</td>
</tr>
<tr>
<td>S within-group error</td>
<td>111</td>
<td>25,025.76</td>
<td>0.005</td>
</tr>
<tr>
<td>Within subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block (B)</td>
<td>1</td>
<td>44.33**</td>
<td>4.80*</td>
</tr>
<tr>
<td>B x W</td>
<td>1</td>
<td>0.96</td>
<td>0.00</td>
</tr>
<tr>
<td>B x P</td>
<td>1</td>
<td>1.92</td>
<td>0.67</td>
</tr>
<tr>
<td>B x W x P</td>
<td>1</td>
<td>0.23</td>
<td>0.00</td>
</tr>
<tr>
<td>B x S within-group error</td>
<td>111</td>
<td>3,186.04</td>
<td>0.002</td>
</tr>
</tbody>
</table>

Note. Mean square errors are in parentheses. S = subjects.

*p < .10.  **p < .01.
Appendix C

Experiment 1a: Analysis of Variance Summary Table for Ambiguous-Association Learning Under Different Workload and Perceptual Requirement Conditions

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>RT</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workload (W)</td>
<td>1</td>
<td>2.39</td>
<td>0.27</td>
</tr>
<tr>
<td>Perceptual Requirement (P)</td>
<td>1</td>
<td>92.18**</td>
<td>29.39**</td>
</tr>
<tr>
<td>W x P</td>
<td>1</td>
<td>2.01</td>
<td>0.01</td>
</tr>
<tr>
<td>$S$ within-group error</td>
<td>111</td>
<td>(23,246.48)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Within subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block (B)</td>
<td>1</td>
<td>15.93**</td>
<td>5.43*</td>
</tr>
<tr>
<td>B x W</td>
<td>1</td>
<td>0.07</td>
<td>0.14</td>
</tr>
<tr>
<td>B x P</td>
<td>1</td>
<td>0.36</td>
<td>0.40</td>
</tr>
<tr>
<td>B x W x P</td>
<td>1</td>
<td>0.18</td>
<td>1.01</td>
</tr>
<tr>
<td>B x $S$ within-group error</td>
<td>111</td>
<td>(1,318.03)</td>
<td>(0.001)</td>
</tr>
</tbody>
</table>

*Note.* Mean square errors are in parentheses. $S$ = subjects.

*p < .05.  **p < .01.
Appendix D

Experiment 1b: Analysis of Variance Summary Table
for Sequence Learning Under Different
Workload and Learning Mode Conditions

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>RT</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Between subjects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workload (W)</td>
<td>1</td>
<td>3.32*</td>
<td>0.17</td>
</tr>
<tr>
<td>Learning Mode (LM)</td>
<td>1</td>
<td>3.35*</td>
<td>0.66</td>
</tr>
<tr>
<td>W x LM</td>
<td>1</td>
<td>0.72</td>
<td>0.90</td>
</tr>
<tr>
<td>$S$ within-group error</td>
<td>106</td>
<td>(30,787.96)</td>
<td>(0.007)</td>
</tr>
<tr>
<td><strong>Within subjects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block (B)</td>
<td>1</td>
<td>15.19**</td>
<td>2.96*</td>
</tr>
<tr>
<td>B x W</td>
<td>1</td>
<td>0.91</td>
<td>0.04</td>
</tr>
<tr>
<td>B x LM</td>
<td>1</td>
<td>3.65*</td>
<td>0.00</td>
</tr>
<tr>
<td>B x W x LM</td>
<td>1</td>
<td>1.12</td>
<td>0.79</td>
</tr>
<tr>
<td>B x $S$ within-group error</td>
<td>106</td>
<td>(6,639.73)</td>
<td>(0.003)</td>
</tr>
</tbody>
</table>

Note. Mean square errors are in parentheses. $S = \text{subjects}$.

*p < .10.  *p < .05.  **p < .01.
Appendix E

Experiment 1b: Analysis of Variance Summary Table for Unique-Association Learning Under Different Workload and Learning Mode Conditions

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>RT</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workload (W)</td>
<td>1</td>
<td>4.17*</td>
<td>0.19</td>
</tr>
<tr>
<td>Learning Mode (LM)</td>
<td>1</td>
<td>2.29</td>
<td>0.44</td>
</tr>
<tr>
<td>W x LM</td>
<td>1</td>
<td>0.77</td>
<td>0.00</td>
</tr>
<tr>
<td>S within-group error</td>
<td>106</td>
<td>(33,740.51)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Within subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block (B)</td>
<td>1</td>
<td>18.90**</td>
<td>6.15*</td>
</tr>
<tr>
<td>B x W</td>
<td>1</td>
<td>1.26</td>
<td>0.01</td>
</tr>
<tr>
<td>B x LM</td>
<td>1</td>
<td>1.49</td>
<td>2.43</td>
</tr>
<tr>
<td>B x W x LM</td>
<td>1</td>
<td>0.65</td>
<td>0.01</td>
</tr>
<tr>
<td>B x S within-group error</td>
<td>106</td>
<td>(8,648.07)</td>
<td>(0.004)</td>
</tr>
</tbody>
</table>

**Note.** Mean square errors are in parentheses. S = subjects.

*p < .05. **p < .01.
Appendix F

Experiment 1b: Analysis of Variance Summary Table for Ambiguous-Association Learning Under Different Workload and Learning Mode Conditions

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>RT</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participants</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workload (W)</td>
<td>1</td>
<td>2.79*</td>
<td>0.44</td>
</tr>
<tr>
<td>Learning Mode (LM)</td>
<td>1</td>
<td>3.63*</td>
<td>0.57</td>
</tr>
<tr>
<td>W x LM</td>
<td>1</td>
<td>0.67</td>
<td>0.02</td>
</tr>
<tr>
<td>Subjects within-group error</td>
<td>106</td>
<td>(31,617.63)</td>
<td>(0.008)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>RT</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Within subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block (B)</td>
<td>1</td>
<td>12.43**</td>
<td>1.51</td>
</tr>
<tr>
<td>B x W</td>
<td>1</td>
<td>0.66</td>
<td>0.07</td>
</tr>
<tr>
<td>B x LM</td>
<td>1</td>
<td>4.26*</td>
<td>0.39</td>
</tr>
<tr>
<td>B x W x LM</td>
<td>1</td>
<td>1.22</td>
<td>1.29</td>
</tr>
<tr>
<td>B x Subjects within-group error</td>
<td>106</td>
<td>(6,772.98)</td>
<td>(0.003)</td>
</tr>
</tbody>
</table>

Note. Mean square errors are in parentheses. S = subjects.

*p < .10.  *p < .05.  **p < .01.
## Appendix G

### Experiment 1c: Analysis of Variance Summary Tables for Learning All, Unique, and Ambiguous Sequence Associations

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>RT</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>I. All Associations</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>F</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Source</td>
<td>df</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block (B)</td>
<td>1</td>
<td>0.12</td>
<td>3.20</td>
</tr>
<tr>
<td>B x S within-group error</td>
<td>19</td>
<td>7.507</td>
<td>0.001</td>
</tr>
<tr>
<td><strong>II. Ambiguous Associations</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>F</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Source</td>
<td>df</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block (B)</td>
<td>1</td>
<td>11.27</td>
<td>0.13</td>
</tr>
<tr>
<td>B x S within-group error</td>
<td>19</td>
<td>6.523</td>
<td>0.001</td>
</tr>
<tr>
<td><strong>III. Unique Associations</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>F</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Source</td>
<td>df</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block (B)</td>
<td>1</td>
<td>12.27</td>
<td>4.35*</td>
</tr>
<tr>
<td>B x S within-group error</td>
<td>19</td>
<td>26.221</td>
<td>0.003</td>
</tr>
</tbody>
</table>

**Note.** Mean square errors are in parentheses. $S =$ subjects.

$p < .10$.  **$p < .01$.**
Appendix H
Analysis of Variance Summary Table
for Sequence Learning in Experiment 1d

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>RT</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Within subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block (B)</td>
<td>1</td>
<td>1.87</td>
<td>1.36</td>
</tr>
<tr>
<td>B x $S$ within-group error</td>
<td>13</td>
<td>(2,100.50)</td>
<td>(0.0006)</td>
</tr>
</tbody>
</table>

**Note.** Mean square errors are in parentheses. $S$ = subjects.
Appendix I
Analysis of Variance Summary Tables for Learning All and Unique Sequence Associations in Experiment 2

I. All Associations

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>RT</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Condition (C)</td>
<td>2</td>
<td>17.43**</td>
<td>4.64*</td>
</tr>
<tr>
<td>$S$ within-group error</td>
<td>61</td>
<td>(19,207.91)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Within subjects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block (B)</td>
<td>1</td>
<td>2.49</td>
<td>3.64x</td>
</tr>
<tr>
<td>B x C</td>
<td>2</td>
<td>2.33</td>
<td>0.15</td>
</tr>
<tr>
<td>B x $S$ within-group error</td>
<td>61</td>
<td>(879.00)</td>
<td>(0.0006)</td>
</tr>
</tbody>
</table>

Note. Mean square errors are in parentheses. $S$ = subjects.

$x_p < .10. \quad *p < .05. \quad **p < .01.$
II. Unique Associations

<table>
<thead>
<tr>
<th>Source</th>
<th>df</th>
<th>RT</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Between subjects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Condition (C)</td>
<td>2</td>
<td>11.13**</td>
<td>0.29</td>
</tr>
<tr>
<td>$S$ within-group error</td>
<td>61</td>
<td>(21,209.88)</td>
<td>(0.004)</td>
</tr>
<tr>
<td><strong>Within subjects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block (B)</td>
<td>1</td>
<td>0.45</td>
<td>5.84*</td>
</tr>
<tr>
<td>B x C</td>
<td>2</td>
<td>6.74**</td>
<td>4.61*</td>
</tr>
<tr>
<td>B x $S$ within-group error</td>
<td>61</td>
<td>(2,329.33)</td>
<td>(0.002)</td>
</tr>
</tbody>
</table>

Note. Mean square errors are in parentheses. $S$ = subjects.

$p < .10. \ \ \ \ *p < .05. \ \ \ **p < .01.$