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A Time-Series Analysis Of Implicit Learning And Tacit Knowledge And The Heuristic Value Of Methods Used To Substantiate The Cognitive Unconscious

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A TIME-SERIES ANALYSIS OF IMPLICIT LEARNING AND TACIT KNOWLEDGE AND THE HEURISTIC VALUE OF METHODS USED TO SUBSTANTIATE THE COGNITIVE UNCONSCIOUS

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ABSTACT

Two central topics of debate persist in the field of implicit learning (IL): (1) whether learning and the subsequent knowledge acquired during artificial grammar learning (AGL) tasks are best characterized as conscious or unconscious, (2) whether the acquired knowledge is bound more to physical characteristics of the stimuli or is more abstract in nature. Participants in this study received extensive training with nonsense letter strings (e.g., VJTVXJ). All strings were seemingly random, but some contained a pattern that could be detected. Results indicated that chunks of information made available in the letter strings were accessible to passive and active learning mechanisms, which led to the development of abstract knowledge that can best be characterized as intuition. The experimental design was such as to encourage either conscious or unconscious knowledge. Subjective measures and post-tests were used to distinguish the difference. All corresponded well, providing evidence of their validity and of their heuristic value for establishing evidence of unconscious cognitive processes.

Keywords: implicit learning, tacit knowledge, subjective measures, PDP

DEDICATION

This work is dedicated to my daughter Sofia Grace Streeter. She is an amazing little person and will always carry a large piece of my heart with her.

LIST OF ABBREVIATIONS AND SYMBOLS

IL	Implicit learning
BCS	Balanced chunk strength
PDP	Process dissociation procedure
CS	Chunk strength
SD	Standard deviation
SE	Standard error
p	Probability
ANOVA	Analysis of variance
η_p^2	Partial eta squared
AG	Artificial grammar
AGL	Artificial grammar learning

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I would like to thank my family and friends for their support over the years. I'd like to extend special thanks to my good friend and colleague, Kenji Noguchi, for his insight and more importantly, his sense of humor. And to David Shirley, whose wisdom has been and will continue to be invaluable.

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INTRODUCTION

Implicit learning (IL) is a term conceived by Reber (1967) to describe learning recognized in his first artificial grammar learning (AGL) tasks. Reber's original description of IL included unconscious and abstract characterizations. These characterizations are the principal focus of the current research. Both have been the topic of numerous ongoing debates. The AGL transfer task paradigm has proven very useful at addressing the role of consciousness and the type of knowledge representations that IL creates. This study employed a variant of the AGL paradigm designed to include manipulations that will best address these issues. Methods that have been advanced in direct response to past (and on-going) criticisms were also incorporated into the design. Of these criticisms, appropriate control conditions and valid measures of consciousness have been points of persistent contention. This study incorporated the most empirically valid control conditions and measures of consciousness suggested to date. A time-series design was used to provide for higher levels of training and skill development, as investigators in the field have argued that such experiments are greatly needed (Mathews, 1997; Dienes, 2008; Johanson, 2009).

BACKGROUND

The definition of IL has met many challenges since the introduction of the concept by Reber (1967). Frensch (1998), who addressed this issue at length, defines IL as "the non-intentional and automatic acquisition of knowledge about structural relations between objects or events" (p.96). This is an intentionally neutral definition as it does not mention consciousness, nor does it address the exact nature of the IL-acquired knowledge—the more contentious components of the on-going debate. The consensus maintained is that IL operates largely outside of consciousness and is abstract in (some) form. IL is characterized by the following: (a) adaptation to detected environmental patterns without the intention to learn from such regularities, (b) the acquisition of knowledge of which the individual lacks a definitive sense of awareness, and (c) the lack of processing typically ascribed to conscious learning conditions, such as hypothesis-testing or making inferences (Perruchet and Pacton, 2006). These three characteristics taken together can be used to formulate an operational definition of IL that provides for quantifiable measures of both unconscious knowledge and learning, as well as for representational form.

Researchers have not reached consensus on an operational definition for the cognitive unconscious because definitions vary based on the measures used to establish consciousness itself (Destrebecqz and Peigneux, 2005). However, an operational definition for consciousness can be framed by applying assumptions based in theories of consciousness. *Higher-order Thought* (HOT) theories are presupposed when Dienes (1997) suggests that two basic criteria must be established to indicate unconscious knowledge: (1) the presence of knowledge, (2) the lack of *metaknowledge* (i.e., knowledge of knowledge). Establishing an operational definition for conscious processes also benefits from the degree of consensus that has been established on the conscious nature of working memory (WM). WM is traditionally defined as immediate memory with active elements such as perceptual input, rehearsal, and recall (Baddeley, 1998); elements theorized to be verbally accessible (e.g., Baars, 2002). WM has also been linked to conscious (explicit) learning processes such as hypothesis testing and drawing inferences (Dienes, 2008a). Another characteristic of consciousness includes the ability to *control* the use of acquired knowledge (Jacoby, 1991). Based on these characteristics, consciousness knowledge can be generally defined as knowledge that an individual is aware of, that is verbally accessible, able to be recalled, and can be controlled. The cognitive unconscious, then, can be defined by performance measures that lack the characteristics used to define consciousness. Thus, a working operational definition of unconscious knowledge can be stated as follows: *Unconscious (i.e., Tacit) knowledge is knowledge that an individual is unaware of, that is inaccessible to verbal report and recall, and is outside of an individual's control.* This definition establishes the need for indirect measures. Three indirect measures are described in later sections that were employed in the current research in an effort to assess the unconscious nature and representational form of IL and tacit knowledge.

The Artificial Grammar Learning Paradigm

The artificial grammar learning (AGL) paradigm has been the most widely used method to research IL and tacit knowledge. In these studies, some variety of a finite-state artificial (i.e., nonsense) grammar (Figure 1) is used to generate a series of elements (e.g., a string of letters of a particular length exemplifying an instantiation of the grammar, otherwise referred to as a grammar *exemplar*) where the order of the elements is governed by a complex set of rules described by the grammar (e.g., Reber, 1967).

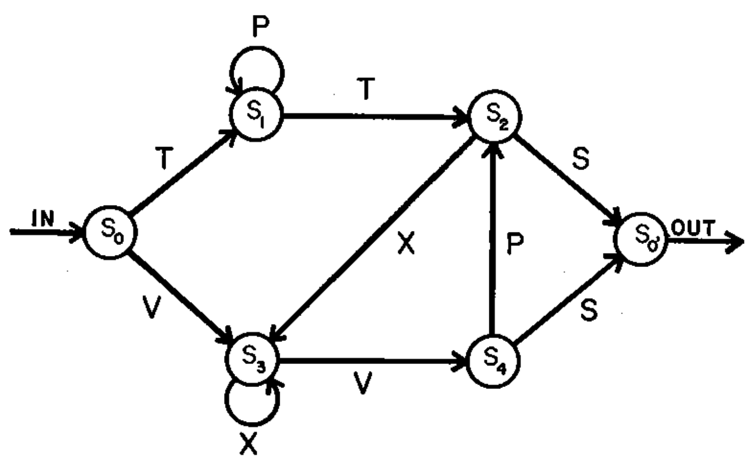

Figure 1. Pictured is the artificial grammar used by Reber (1965, p. 856) to generate test exemplars. The exemplar VXVS is constructed by beginning with V at the left and adding the letters X, V, and S as you proceed to the right. TXSP would be considered a non-grammatical string because it cannot be constructed by taking any path through the grammar.

AGL studies traditionally involve two stages: a learning stage where participants are asked to memorize a subset of exemplars generated by the grammar, and a testing phase where participants are informed that sequences were rule-governed (though are not informed of the rule). Following training and immediately before testing, participants are informed of the rule-governed structure of the grammatical exemplars. They are then presented with a series of testing exemplars, only half of which obey the rules of the grammar, and are asked to determine which exemplars match the rules (e.g., Reber, 1967). Participant performance is usually above chance (typically 60%-70%) in the classification task, despite difficulty by the participants to describe how they performed the classification task (Mathews et al., 1989; Reber, 1967). This above-chance performance has been attributed to participants having learned implicitly (i.e., unconsciously) the abstract, representational rules that govern the structure of the grammar (Reber, 1993). Debates center on whether abstract knowledge representations are acquired or whether knowledge is bound to the perceptual[1] features of the stimuli. To phrase it another way, 'abstract' refers to a form of representation that is not bound directly to stimulus characteristics (e.g., a letter or a particular font) but rather involves the acquisition of the 'deep' rules of the AG employed to create exemplars. This distinction is tested traditionally by employing AGL transfer tasks, where the identical AG is used to create training and testing exemplars with different perceptual domains (e.g., a switch in letter set). The following section provides a description of the three core representational models of IL-acquired knowledge.

Representational Form of the Knowledge Acquired during an AGL Task

A number of models have been suggested for the form of cognitive representation that is acquired during AGL tasks. Three core models are offered below that range from stimulus-specific to abstract forms of representation. In this context, abstract is defined along its own continuum. At one end, abstract representations are more closely bound to stimulus characteristics. At the other end, representations are characterized almost exclusively by symbolic representations. As has been consistently recognized over the

[1] The term 'perceptual' refers to that part of perception bound to the immediate sensory experience.

years (Reber, 1989, 1993; Greenwald, 1992; Frensch, 1998; Pothos, 2007), a considerable literature exists in support of each of the models.

The Exemplar Based View

Exemplar-based models suggest that when stimuli are encountered a ‘raw’ form of each stimulus is encoded, establishing a large memory of stored exemplars, which can then be used to determine grammaticality through comparison of novel stimuli to those stored in memory (Brooks and Vokey, 1991; Manza and Reber, 1997). According to the exemplar view, similarities are detected between trained and tested stimuli and compared by ‘analogy’ (i.e., a stored exemplar is found to be analogous to a novel one) rather than the learning of abstract, algebra-like[2] rules (Brooks and Vokey, 1991).

In this sense, exemplar based models do have an abstract component, which is the ability to compare exemplars through the process of analogy. However, the process of comparing exemplars based on abstract analogies is more closely bound to the stimulus characteristics and does not require the creation of symbolic representations of the exemplar components (e.g., algebra-like variables). This conceptual distinction regarding “abstract” is the topic of much of the representational debate and was addressed in the current research. Exemplar-based views represent holistic theory, as whole exemplars are encoded (Reber, 1997). They are contrasted against the chunk theories presented next.

Fragmentary Account of ‘Chunks’ of Information

The term *chunking* refers to the process of breaking complex stimuli (e.g., exemplars) into fragments that are more accessible for encoding. The general challenge

[2] The term ‘algebra-like’ refers to the process of learning through the abstraction of variables that *represent* elemental stimuli, rather than learning being bound solely to stimuli. This abstract variable-form can then be used to establish rules of operation and co-variant relationships, which can be generalized to other stimulus structures (e.g., stimuli composed of different letter types, or even non-letter stimuli, such as shapes or sounds).

to both the abstractionist view and the exemplar view described above is that an account for learning and transfer of learning can be based on the detection of two and three element groupings that are present in both training and testing exemplars (Manza and Reber, 1997). A variety of models exist that suggest some form of chunking that is involved in AGL, each providing different interpretations of the use of chunks (e.g., Perruchet and Peacteau, 1990; Servan-Schreiber and Anderson, 1990; see Reber, 1993 for review).

The *Competitive Chunking Network* (CCN) model described by Servan-Schreiber and Anderson (1990) suggests that chunks are arranged in hierarchical fashion from small, two and three element groups, to larger chunks that eventually establish a memorial representation of longer grammatical exemplars. The PARSER model advanced by Perruchet and Pacteau (1990) similarly relies upon chunks, but in their case, the chunks are used to create rules for the grammaticality of exemplars. The rules in PARSER are still bound to the stimulus features and thus are contrasted against the algebra-like abstraction indicative of Reber rules (cf. Reber, 1989a, 1993). To clarify, Vokey and Brooks (1991) characterize PARSER rules as "relational or abstract analogy to prior instances, rather than to implicitly abstracted knowledge" (p. 321). PARSER represents a *localist* representation in that learning is bound to co-occurring elements (i.e., chunks), though other chunking model provide for more *distributed* representations that allow for increasingly more complex forms of representation (Boucher and Dienes, 2003). Hybrid models have also been developed where knowledge acquired in an AGL study is comprised of both chunks and some abstract features (e.g., detection of symmetry across halves of the letter string— PTTT.CXXX) of the stimulus display

(Mathews, et al., 1989). Most exemplar or episodic accounts of IL have assumed that the knowledge of exemplars or episodes that is acquired during training is explicit or conscious (e.g., Perruchet and Pacteau, 1990; Shanks and St. John, 1994). This assumption is rarely put to the test (Berry, 1997). The current research addressed directly the role chunks play in the learning found in AGL tasks by controlling chunk position during training and classification tasks (described below). By this method, the extent to which chunk-based information is relied upon to make grammaticality judgments can be determined, along with the conscious or unconscious nature of this knowledge.

The Abstractionist View

Implicitly acquired knowledge has long been considered abstract and independent of stimulus form, perceptual domain, and sensory modality (Reber, 1985, 1989, 1993; McAndrews and Moscovitch, 1985; Allen and Reber, 1980). In this particular view, the emphasis has been on the structural relationships among stimuli that establish a 'deep' abstract representational form of knowledge that is not bound directly to specific physical characteristics of the stimuli (Reber, 1985). One of the more appealing aspects of the abstractive view is that it endures as a reasonable account for learning observed in transfer tasks (Reber, 1993).

Chunks and the Abstractionist View. As has been established above, the process of chunking information is well represented in models of IL (at least as explanatory for learning in AGL studies). The process of chunking may also have intuitive appeal in that humans often learn through the process of associating elements into novel entities. Indeed, Reber (1989a) maintains an important role of detecting simple associations in his abstractionist account, where unconscious knowledge is established based on such associations (Reber, 1989a). Vokey and Brooks (1991) provide a context for the theoretical distinctions described above:

> Obviously, humans are capable of forming and using abstract knowledge. However, one cannot merely assume that the unquestioned existence of human abstract ability means that performance in [AGL] is based on abstract knowledge without forfeiting any possibility of discovering the conditions under which abstract knowledge is formed (p. 321).

This consideration does not refute the possibility of abstract forms of knowledge; it suggests that if learning can be described by other means, then these means should be entertained. As has been observed, all of the preceding views are supported in the existing literature and each may be a more or less appropriate description of data depending on the experimental technique used to generate behavioral data (Reber, 1997).

Domain Transfer Studies with Artificial Grammars

Domain transfer studies involve a switch in domain from training to testing conditions (e.g., a switch to a different set of letters at testing than was used during training). If knowledge is applied successfully despite a shift in perceptual domain, it can be suggested that it has an abstract representational form (Reber, 1989). The ability to classify exemplars at levels well above chance, despite changes in letter set, has been consistently recognized in the literature (e.g., Reber & Allen, 1978; Reber & Lewis, 1977; Manza and Reber, 1998; Mathews et al., 1989; Brooks and Vokey, 1991; Whittlesea and Dorken, 1993).

Three instructional manipulations are commonly used in transfer studies to establish learning conditions that either promote or discourage the conscious use of chunk information. Observation instructions ask participants to simply attend to exemplars generated by the AG; these instructions are used to establish *incidental* learning conditions (Brooks and Vokey, 1991; Perruchet and Pacteau, 1990; Reber et al., 1980). Incidental learning conditions are theorized to promote IL and tacit knowledge of a more abstract nature (Reber, 1989). Memorization instructions require participants to memorize and reproduce exemplars in accordance with some specified performance criterion (Reber, 1969; Reber and Lewis, 1977). Participants are not informed of the rules of the grammar; hence, these instructions have also been used to establish incidental learning conditions. However, since this instructional manipulation encourages the use of memorization strategies, knowledge may be more conscious and thus more explicit in nature (Reber, 1989). Rule-searching instructions ask that participants actively search for the underlying grammatical rules used to construct exemplars (e.g., Mathews et al., 1989). Instructions of this kind are meant to encourage *intentional* learning strategies (e.g., making associations and inferences or hypothesis testing) that are consciously available and thus able to be described (Reber, 1989). In sum, observational and memorization instructions are employed to encourage incidental learning (i.e., implicit learning) and unconscious knowledge, whereas rule-search instructions are meant to promote intentional learning (i.e., explicit learning) and conscious knowledge (Shanks and St. John, 1994).

An instruction manipulation is proposed for the present study for the purposes of creating the most distinct incidental and intentional learning conditions possible. As has been hypothesized, observation-only instructions promote incidental learning better than memorization instructions because the latter may encourage intentional learning through the application of memorizing strategies (Reber, 1989). However, simply asking participants to observe exemplars over extended training may lead to a lax in participant motivation (i.e., sitting in front of computer monitor for extended periods of time just staring at nonsense exemplars might lead to "mind wandering"; Reber, 1989). In an effort to encourage incidental learning (and thus abstraction) and to address possible motivation concerns, "familiarize" instructions will be given to participants. In this way, training should be more engaging for the participants, while reducing the chance of a memory-strategy confound. Moreover, recent studies addressing familiarity have shown that it is often associated with unconscious knowledge (Scott and Dienes, 2008; 2010). The main consideration with these manipulations is to encourage as much abstract and unconscious knowledge as possible in the incidental learning conditions, this, in order to provide the best contrast to the explicit and conscious knowledge in intentional learning conditions. By this method, measures of consciousness can determine best which processes are operating across training and transfer test conditions. Familiarity judgments will be asked of participants during training and are a non-invasive way to collect data in incidental learning conditions (Scott and Dienes, 2008). The task of determining if an exemplar is more or less familiar does not alter the task as much as, say, asking participants in the memorization condition to make grammaticality judgments (Reber, 1989). In this way, learning and knowledge acquired during training in the incidental learning conditions can be tracked over time and compared to intentional learning conditions. This is one of the more appealing methods of the Mathews et al. research design, against which this study was patterned.

Mathews et al., 1989 Study

The current study was patterned roughly against the Mathews et al. (1989) AGL transfer study (Experiments 1&3). The Mathews study tested a variety of IL characteristics, including the abstract and unconscious nature of IL and tacit knowledge that are the focus this research. Mathews provided two instruction conditions, memory-based (incidental) and rule-search (intentional) instructions, extended training over a four-week period, and employed yoked participants throughout. Participants in the memory-based condition were asked to memorize exemplars during training to prepare for a memory test to be given each week. This was the incidental learning condition and it was expected that it would promote IL of the underlying grammatical structure. Participants in rule-search conditions were told from the start that the exemplars were constructed based on a complex set of rules and to try to determine the nature of the rules. This intentional learning condition, it was hypothesized, would promote explicit learning based on bi- and trigram chunks. On each of the 4 weeks, participants were first trained with a list of 20 grammatical exemplars and were then given 200 classification trials at test. In this way, a measure of learning over time was provided and each testing condition served as additional training condition (an intent of the design). Importantly, Mathews extended the incidental learning condition over a 3-week period (a new method at the time). As opposed to being informed that exemplars were rule governed before testing in the incidental condition, as is standard, this information was withheld until the final week of testing. All prior weeks of testing asked participants to make "similarity" rather than grammaticality judgments. It was suggested that similarity judgments would not create situations where participants would shift to a rule-searching strategy to make grammaticality judgments, effectively frustrating any further incidental learning.

Training and testing conditions each week shared the following characteristics. Participants were asked to study 20 valid strings and were then presented with a five alternate-forced-choice (AFC) task consisting of one grammatical exemplar and four ungrammatical exemplars with 1, 2, 3, or 4 grammatical violations. This method was employed to detect early learning that may not be detected by providing only two choices (i.e., a 2-AFC task). It was hypothesized that participants would select exemplars with fewer violations over training. This hypothesis held.

Yoked participants were used in the Mathews study to measure explicit knowledge. In the yoked conditions, participant "instructors" were asked to provide instructions about how they were making their classification judgments to another 'unseen' participant. They were informed that their instructions would be the only thing used by their yoked counterparts to make their grammaticality judgments. Yoked conditions were used only under rule-search conditions, as asking participants to describe what makes exemplars 'similar' in the incidental conditions confounds the implicit condition by asking for explicit knowledge. Memory-based learners were told before the final week of testing that exemplars were rule-governed before classifying. All participants in each experimental condition were yoked in the final week.

As described, the testing condition extended over a 4-week period in the Mathews study, measuring classification performance each week in all conditions. This method provided an opportunity to track learning during training and testing over time, with the additional manipulation of having yoked participants paired from week one in the rule-search condition. Taken together, these methods provided an "online" measure of the effect of training, rather than to wait until training was completed by taking an "offline" measure during testing. Changes in explicit knowledge were tracked with yoked participants, as explicit knowledge accessible to instructors should be available to be transferred to their yoked counter parts. The expected effect of instructional condition and the availability of knowledge were both realized in the study (Table 1).

Condition	Week 1	Week 2	Week 3	Transfer Week 4
Memory-same set				
Experimental	5.07	1.86	.82	2.22
Week 4 Yoked	--	--	--	5.36
Memory-different set				
Experimental	6.32	5.18	4.96	3.04
Week 4 Yoked	--	--	--	5.32
Rule-same set				
Experimental	6.82	3.14	2.14	3.03
Week 1-3 Yoked	8.82	6.25	5.21	3.46
Week 4 Yoked	--	--	--	5.57
Rule-different				
Experimental	7.14	4.46	3.75	2.07
Week 1-3 Yoked	8.75	5.64	5.71	3.00
Week 4 Yoked	--	--	--	5.18
Control-same set	8.86	8.86	9.18	9.90
Control different set	9.14	9.82	9.28	9.90

Table 1. The expected value of chance performance is 10 violations. All groups in the Mathews et al. study displayed learning and transfer of learning. Yoked performance shows that some but not all of the knowledge acquired in the intentional learning conditions is available for explicit description.

The *teach-aloud* procedure (Mathews et al., 1989) had participants periodically stop while working on the primary task (e.g., trying to discriminate valid from invalid grammar exemplars) to give verbal instructions for someone else (i.e., yoked participants) to perform the task. The main advantage of the teach-aloud procedure is that the relative level of performance of yoked participants versus their experimental partners provides a direct measure of the extent to which knowledge of the grammar can be communicated verbally to another person—a measure of their explicit knowledge of the grammar. If the verbal reports are obtained frequently enough, a satisfactory empirical account of participants' online awareness of their processing strategies during the task can be obtained (Mathews et al., 1989). Yoked participants also provide a no-training condition, which has been lacking in earlier studies and has been an issue of contention for some researchers in the field (e.g., Redington and Chater, 1996). Yoke conditions were employed that were very much in line with the Mathews study and are described in the methods section.

The current research design varied in a number of ways from the Mathews study. The familiarity condition in the current study served the exact same function as the Mathews similarity condition. However, familiarity judgments were required instead of similarity judgments because the latter might involve associations, which could encourage explicit processing (Reber, 1993; Dienes & Scott, 2010). A two-alternative forced choice (2-AFC) task replaced the 5-AFC used in the Mathews study. It has been suggested that forcing participants to compare only two exemplars maximizes the opportunity for participants to utilize chunk information (Shanks, Johnston, and Staggs, 1997). As the *balanced chunk strength* (BCS; described in detail below) design used in the current study is employed to control directly the chunk information available to participants, use of a 2-AFC task (instead of a 5-AFC) should provide for an even more sensitive measure of BCS effects.

The nature of learning and knowledge in the incidental condition was not measured over time in the Mathews study. The subjective measures in the current study serve this very function. Also, the process of collecting online training and testing measures is encouraged in recent literature (Haider, Eichler & Lange, 2010) as a way of accounting for methodological criticisms leveled at the validity and reliability of measurements of consciousness in AGL transfer studies (Shanks and St. John, 1994). A related issue has been recognized in that there are no assurances that knowledge diagnosed during testing is the same knowledge that is used during training (Shanks, et al., 1997). Subjective measures taken across all conditions will address this issue as well, as performance measures should be sensitive enough to compare knowledge across conditions. Additionally, there is no way of knowing whether participants in an incidental learning condition switch to an explicit rule searching strategy, or that participants in intentional learning conditions switch to attempting to discover the underlying grammatical regularities (Haider, Eichler, & Lange, 2010). Online training measures provide a solution to this issue by diagnosing knowledge used during training over time, which can then be used to aid in determining if qualitative differences in learning exist due to experimental manipulations. The indirect measures described below served as the online measures taken during training/testing in the current study. Online training measures can also serve as external criteria, which can be compared to post-experimental knowledge test. This study employed a variation of the *Process Dissociation Procedure* (PDP) as a post-experimental test of knowledge. If the same theoretical construct is being measured (e.g., the cognitive unconscious), then measures should relate to one another.

Balanced Chunk Strength (BCS) Design

It has been found that in most AGL studies, grammatical testing exemplars that are randomly created from the AG have higher *chunk strength* (CS) than non-grammatical exemplars (Perruchet, 1994). In an early address of this issue, Reber and

Allen (1978) asked participants to describe their learning experiences and how they classified exemplars during testing (a measure of explicit knowledge). Responses indicated a strong bias to use violations of bigram chunks, especially those chunks at the beginning and end of exemplars. It was obvious that participant knowledge was chunk-based to some extent and that this knowledge was relied upon to determine grammaticality during testing. Thus, CS-bias represents a confound (if it is determined to be conscious) when attempting to establish an abstractionist account for performance in AGL transfer studies (i.e., the superficial similarity between test and training items could account for participants' abilities to classify grammatical from non-grammatical exemplars). Methods have since been introduced to address this issue directly.

Perruchet (1994) established evidence for this possible confound to abstractionist representational knowledge by analyzing the training and testing exemplars used by Brooks and Vokey (1991; Vokey and Brooks, 1992). This study addressed a related confound, that between similarity and grammaticality of grammatical exemplars, i.e., the similarity between training and test exemplars may effect classification performance, thus confounding an abstractionist account of performance (also addressed with the BCS design). Perruchet performed the following statistical analysis on the Brooks-Vokey exemplars: The frequency of initial and terminal trigrams (and bigrams later in Exp. 4) in each testing exemplar was measured across all training exemplars. These counts were then summed and averaged for each testing string. For example, the test string MXRVM begins with the MXR trigram and terminates with the RVM trigram. As was determined, MXR occurred at the beginning of 5 of the total 16 training exemplars. The terminal trigram RVM occurred 2 times in the training exemplars. The resulting equation (5 +

2)/2 provides the CS of the MXRVM testing string, in this case, 3.5. The mean CS of training and test exemplars are then compared across conditions (Table 3). Perruchet determined that the Brooks and Vokey results could be accounted for by the repetition of trigrams across training and testing exemplars.

Overlap of Initial and Terminal Fragments between Training and Test Strings in Experiments 3 and 4

Experiment		Grammatical Similar (GS) *M*	%	Grammatical Dissimilar (GD) *M*	%	Ungrammatical Similar (US) *M*	%	Ungrammatical Dissimilar (UD) *M*	%
3	Trigrams	4.16	13.00	3.13	9.78	3.28	10.25	2.25	7.03
4	Bigrams	1.36	3.78	0.97	2.69	1.44	4.00	1.19	3.31
	Trigrams	0.44	1.22	0.00	0.00	0.47	1.31	0.11	0.31

Table 3. Pictured is the Perruchet (1994) analysis of Vokey & Brooks (1992) taken from Shanks et al. (1997, p. 237, Table 5). Mean CS compared across conditions show the available tri- and bigram information distinguishing grammatical and ungrammatical test exemplars. The percentages provided were calculated by comparison to the maximum possible overlap where each training exemplar began and ended with the same trigram and each testing exemplar shared the same beginning and ending trigram.

To address this confound, Knowlton and Squire (1996) used a BCS design in which both grammatical and non-grammatical test exemplars have the same average CS. This provides experimenters the opportunity to address effects of rule-based representations that are available to participants during their classification task. The addition of indirect measures will provide theoretically relevant insight into whether rule-based knowledge is conscious or unconscious. Moreover, if participants can classify correctly when exemplars are grammatical but lack similarity to trained items (due to the balancing of surface features bound to chunks), then an abstractionists account for the classification can be advanced. The current study employed the BCS design provided by Knowlton and Squire (1996) to quantify the similarity in surface structure (i.e., bigram and trigram structure) between learning and testing exemplars used in the AGL study.

The CS metric is computed by first determining all possible bigram and trigram chunks in a test exemplar (e.g., the exemplar MTX would have a total of three bigram and trigram chunks—MT, TX, MTX). This procedure is very similar to the Perruchet analysis described. The difference is that Perruchet balanced beginning and terminating bi- and trigrams (often referred to as *salient features*), whereas the Knowlton and Squire CS metric balances all bi- and trigram chunks including those in the central part of exemplars (referred to as *non-salient* features). Chunk strength with the CS metric is determined by the average number times the chunks from a test exemplar appear over all training exemplars. Through this method it can be established which test exemplars resemble training exemplars the most (i.e., test exemplars with 'high' chunk strength). Knowlton and Squire found eventually that chunk strength and rule-based knowledge contribute to determining grammaticality. This joint contribution or mix of abstract and stimulus-specific knowledge is in line with interpretations from a number of other researchers (e.g., Conway & Christiansen, 2006; Manza & Reber, 1997). It was hypothesized this trend would be maintained in the current study, with participants displaying a mix of explicit, stimulus-specific knowledge and implicit, unconscious knowledge in both the intentional and incidental conditions (i.e., some chunk information will be present in all exemplars even with the application of the BCS). Indirect measures are intended to 'tease' these contributions apart, which is one of the more theoretically interesting contributions of this research. Another benefit of employing the BCS design is that it has been used in imaging studies to show activation of distinct regions to abstract and fragmentary knowledge (Lieberman et al., 2006).

The Role of the Cognitive Unconscious in AGL

As has been established, AGL paradigms can be used to explore the enduring questions of the role of consciousness in IL and cognition, and the extent that IL processes involve working memory (i.e., the extent to which IL learning and the acquired knowledge involve learning based on fragmentary chunks and whether they are consciously accessible). Some of these questions are echoed in two concerns offered in Manza and Reber (1997): (1) "can complex structural knowledge be acquired without explicit awareness" or does consciousness invariably intrude, (2) can implicit and explicit be "deeply dissociated" or do they represent variations of a single learning process (Manza and Reber, 1997, p. 77)?

The association between IL and unconscious processing has been a central focus of much IL research and has been the focus of considerable debate in the field (e.g., Dulany et al., 1984; Perruchet & Pacteau, 1990; Reber, 1967, 1989; Shanks & St. John, 1994). This assumption of unconscious processing was derived from results of early IL studies (e.g., Reber, 1967; Reber and Allen, 1978), which found that human behavior conformed to the rule-governed structure of the AG. Since these rules were not available to consciousness, the concept of a cognitive unconscious was created to account for rule extraction. The suggestion that IL leads to unconscious knowledge is still held today (e.g., Dienes, 2008a).

Much of the early conceptual debate addressed the extent to which IL either involved the acquisition of unconscious implicit knowledge or explicit knowledge that is available to consciousness as fragmentary knowledge. These conceptual issues extended the debate to methodological concerns. Key methodological concerns are whether research paradigms can be developed that convincingly and entirely dissociate contributions of implicit and explicit knowledge acquired in IL studies. That is, can distinct qualitative differences be established (Dienes, 2008a)? However, it has been argued convincingly that it is very likely the case that both implicit and explicit processes are involved in any learning and testing condition, and attempts to dissociate completely are untenable, along with all attempts to establish such 'process-purity' (Reber, 1993; Reingold and Merikle, 1988; Jacoby, 1991). This realization led to the application of indirect measures that attempt to determine when conscious and unconscious processes are used.

Indirect Measures of the Cognitive Unconscious

Indirect measures dissociate conscious and non-conscious influences on performance and provide quantitative measures of unconscious influences (Jacoby, 1991; Dienes and Berry, 1997). Without indirect measures, hypotheses suggesting that unconscious abstract knowledge is acquired in an AGL task are left unsupported (Redington and Chater, 1996). It has also been pointed out that transfer studies (e.g., Manza and Reber, 1997; Mathews et al., 1989) often lack indirect measures of unconscious influences (Redington and Chater, 1996), and fewer still employ the subjective measures to be used in the present research (Dienes, 2008a). It has been suggested that more than one indirect measure should be used in research exploring the cognitive unconscious (St. John & Shanks, 1997). The use of more than one indirect measure addresses challenges to utilizing subjective measures, which caution against relying on participants to make the final determination of what characterizes consciousness (e.g., St. John & Shanks, 1997; Whittlesea & Dorken, 1993, 1997). The use of more than one indirect measure is also in line with the suggestion that, due to the complexity of the phenomenon of consciousness, more than one form of measurement should be employed (Seth, 2008). If measures used to test for unconscious and conscious knowledge produce similar outcomes, one can more confidently assert that unconscious knowledge is present.

Subjective Threshold Measures. Subjective measures of consciousness are contrasted against the more traditional use of objective measures. To compare, the objective threshold, as defined in cognitive psychology, is the point at which responses to stimuli presented during a forced choice task reach chance level performance (Cheesman and Merikle, 1984). The objective threshold has been the primary measure used in the past to define the boundary between conscious and unconscious mental processing (e.g., Cheesman and Merikle, 1984), and is the favored measure by those most skeptical of unconscious states (e.g., Shanks and St. John, 1994; Whittlesea and Dorken, 1993, 1997). Subjective thresholds are a measure of an individual's claimed awareness (Cheesman and Merikle, 1984; Dienes, 2008). An unconscious distinction is made when participants report that they are unaware of a stimulus, yet perform at better than chance levels on an objective measure (Cheesman and Merikle, 1984).

As implicit learning is thought to develop specific unconscious knowledge, a qualitative distinction can be established with the use of subjective measures (Dienes, 2008). Dienes (2008) offers that appropriate measures of unconscious knowledge need to show two things: that the participant (a) has knowledge but (b) doesn't know that she has it. Building on Cheesman and Merikle's (1984) application of subjective threshold measures used in subliminal research, Dienes and colleagues have applied the measure in a variety of implicit learning paradigms (Dienes, et al., 1995; Dienes and Berry, 1997; Dienes and Perner, 1998, Dienes, 2008). In these studies, perception is said to be below the subjective threshold when target detection is above chance, but when participants say they cannot detect the target; participants lack metaknowledge of the knowledge they are using to perform at above chance levels (Dienes, 2008). Based on this application, two criteria have been established to provide evidence of unconscious processing: the *guessing criterion* and the *zero correlation criterion*. Both of these measures were employed in the current research.

The guessing criterion is met when participant performance is above baseline, even though participants claim to be guessing in their responses to target stimuli (e.g., Dienes, et al., 1995). The zero correlation criterion is met when participants' confidence measures of their own knowledge and their performance rates are not positively correlated (e.g., performance is statistically above chance and participant confidence is low; Dienes, 1995). Based on the results of the application of these two criteria, Dienes (2008) claims that the criteria actually identify qualitatively different types of knowledge. The basis for this claim rests on assumptions generated by theories of consciousness and the logic proceeding from those assumptions in support of the metaknowledge construct.

Philosophical and Theoretical Assumptions Underlying Subjective Measures

There are assumptions that need to be accepted in order to support the validity of subjective measures. In the subjective sense, the distinction between conscious and unconscious is defined at the level at which an individual has access to knowledge or 'knowing that you know' (Rosenthal, 2005). This meta-knowledge sense of the distinction addresses the phenomenology of individual knowledge (Shanks and St. John, 1994), where consciousness represents knowledge that one is aware of and the unconscious represents mental phenomena that an individual is 'unaware of' (Greenwald, 1992). This distinction employs the transitive use (which always takes an object, i.e., consciousness *of* something, e.g., "I know that I see a tree.") of the term conscious in that it refers to "conscious access to and/or conscious processing of a specific piece of information," rather than the intransitive use, which refers to the state of consciousness (i.e., wakefulness or vigilance; Dehaene and Changeux, 2011, p. 201).

A philosophical basis for the use of subjective measures of mental states is established in a hierarchical framework of first- and second-order mental states. First-order mental states are bound only to interactions with the world (e.g., the initial activation of sensory mechanisms sensitive to motion in visual cortex to a moving object). Second-order mental states are mental states about first-order mental states (e.g., knowing that one is seeing an object in motion). The rationale supporting this distinction is exemplified further concerning blindsight patients, as provided in Dienes 2008a:

> Blindsight patients, who have damage to an area of the cortex called V1, can say whether an object is moving up or down at above 80% accuracy. Yet they often claim not to be seeing, often just to be purely guessing (Weiskrantz, 1997). Our strong intuition is to say the seeing is unconscious precisely because the blindsight patient is not aware of seeing; they do not have an accurate mental state about the mental state of seeing. That is, it is *because* they lack a second-order state (a mental state about a mental state) that it seems right to say their seeing is unconscious (p. 253).

This philosophical groundwork provides the basis for interesting theories of consciousness, such as Baars' *Global Workspace Theory* (GWT), which is a *Higher-Order Thought* (HOT) theory that binds metacognition to explicit knowledge (Baars, 2002). This consideration directly affects how we interpret subjective measures of mental states during AGL tasks[3]. According to Baars (1988), conscious knowledge of something makes such knowledge "globally available," meaning that the knowledge can be combined with any other conscious knowledge. These combinations can be used to make inferences and associations and drive explicit hypothesis testing strategies. Thus, intentional learning conditions (i.e., rule-search conditions) should promote the use of conscious knowledge. Alternatively, unconscious knowledge may be applied in a far more specific way, such as to the detection of basic patterns (e.g., grammatical structure in an AG exemplar). Specifically, if classification performance in incidental learning conditions is statistically better than chance and subjective measures do not recognize conscious knowledge, one can posit that the knowledge used to classify successfully is not consciously available (i.e., it is unconscious). In sum, empirical evidence for the unconscious cannot be established without implementing a theoretical construct of consciousness (Dienes, 2008a). Both the guessing and zero-correlation criteria provide some evidence for two qualitatively distinct processes that differ in functional ways (Haider, Eichler & Lange, 2010). However, both criteria still rely on subjective reports, so it has been suggested that such measures should be combined with other measurement methods (Shanks and St. John, 1994). One additional method has already been introduced—yoked conditions—which are used to measure explicit knowledge. Another method is Jacoby's PDP.

The Process-Dissociation Procedure (PDP).

According to the logic offered by the PDP, conscious and unconscious task

[3] It should be mentioned (and as Dienes, 2008a points out) that even if one does not accept 'high-order' theories, determining if and when metaknowledge is available still has theoretical and applied value (Seth et al., 2008).

processing are qualitatively different things (Jacoby, 1994). Conscious knowledge provides for goal-oriented behaviors that are able to be controlled voluntarily, whereas unconscious knowledge is applied involuntarily (Jacoby, 1994; Destrebecqz and Cleeremans, 2001; Fu, Fu, and Dienes, 2008). Estimates of conscious and unconscious influences can be made by comparing performance on tasks where either both the conscious and unconscious contribute to a task—the *inclusion* task—or are set in opposition to each other—the *exclusion* task (Cleeremans et al., 1998). Examples of these tasks are as follows. In an inclusion task participants are asked to generate a sequence that most closely resembles the one upon which they were previously trained (e.g., Buchner et al., 1998). During this task they can either rely on recollection, the conscious knowledge (C), or they can guess based on unconscious knowledge (UC), such as that based on intuition; both conscious and unconscious knowledge are operable and work in unison (C+UC; Jacoby, 1991). In an exclusion task, participants are directed to produce a sequence that is as different as possible from the training sequence (e.g., Buchner et al., 1998). Such a task sets unconscious and conscious influences in opposition to each other because knowledge of the trained sequence is required in order to produce *novel* sequences (Jacoby, 1991). If participants continue to generate the trained sequences during the exclusion task, it is taken as evidence of the influence of U (Jacoby, 1991). A measure of the influence of C can then be determined by computing the difference in performance on the two tasks and a measure of U can be determined based on how much performance on the exclusion task exceeds this baseline (Jacoby, 1991). In other words, participants either try to avoid applying knowledge (as in the exclusion task) or try to apply all knowledge (as in the inclusion task); differences recorded between these two conditions indicate conscious knowledge, and use of knowledge despite intentions indicates unconscious knowledge (Jacoby, 1991).

A variant of the PDP was used in a serial reaction time (SRT) IL task by Destrebecqz and Cleeremans (2001, 2003). In these studies, stimuli were presented sequentially (i.e., one stimulus on each trial) in one of four locations on a computer screen. Participants were then asked to record the location of each stimulus by pressing a button corresponding to each of the four locations. Unknown to the participants, sequences were structured based on a rule-governed pattern (just as rules govern grammatical structure in AGL exemplars). According to SRT logic, learning is evidenced if participants press the correct button at faster and faster rates. In this case, faster response rates when sequences followed the pattern compared to when they violated it would indicate learning. This was found to be the case and the conscious nature of this learning was then tested with a PDP variant. Participants were asked to generate sequences in an inclusion task by being told to try to replicate as best as possible the sequence they had learned during training. In the exclusion task, they were asked to do just the opposite and try not to generate trained sequences. Participants were unable to suppress knowledge in this condition and generated trained sequences at levels above chance. This indicated a lack of control over the applied knowledge, suggesting that the knowledge was unconscious according to PDP logic.

The current experiment used a modified version of Jacoby's PDP task that is in line with suggestions from investigators in the field of AGL (Shanks and St. John, 1994; Wilkinson and Shanks, 2004; Dienes, 2008a). The recommended procedure is a string completion task where exemplars are taken from trained exemplars. The inclusion portion of the task asks that participants attempt to replicate trained exemplars as best as possible. Participants are advised to use any knowledge that they have gained, whether it is knowledge that they know they know or just feel like they know. In the exclusion task, they are asked to do the opposite and complete exemplars so that they are as dissimilar as possible from trained exemplars. Grammatical exemplars created in the exclusion condition represent a failure to suppress knowledge gained during training. This would indicate that the knowledge applied is unconscious.

EXPERIMENT

The following research design was roughly patterned against Mathews et al., (1989). Departures from the Mathews study include the following: (1) substituting the memory-based instructions with "familiarize" instructions, (2) to apply subjective measures during the training and testing conditions, (3) use of the PDP, and (4) a balanced chunk strength manipulation. The grammar to be used is taken from Brooks and Vokey, 1991. Exemplars from that grammar were balanced for chunk strength with the Knowlton and Squire chunk metric (1996). Subjective measures were applied according to Dienes (2008a). A modification to Jacoby's PDP (1991) was used in accordance with Shanks (2005) suggestions. With few exceptions, the proposed analyses were similar to those used in the AGL studies from which each manipulation was patterned.

Participants and Design.

The basic design of the current study is a 2 (rule-search v. familiarization instructions) X 2 (BCS versus no-BCS) X 3 (Time) mixed model ANOVA. Power analysis indicated an ideal n = 22 for each of the 12 groups (4 experimental, 4 single week yoked, 2 fully yoked, 2 fully yoked controls). Due to attrition rates, the actual numbers varied slightly across groups, with an eventual total of N = 223 participants. Experimental participants were trained and then tested on the same day and time each week, repeated over a three-week period (except for final-week yoked participants who tested only once). Fully yoked participants (i.e., three-week yoked) were paired with each rule-search participant starting at week one and were only provided their paired 'instructor' descriptions to classify exemplars. Four single-day yoked groups were paired with each experimental group on the final week.

There is some contention about whether control groups are necessary for each experimental condition or whether performance can be compared against the chance proportion of .50 (Perruchet, 1994). The contention is based on two concerns, the first of which refers to learning that may be present during testing, which is encouraged in the present design (and measured in the yoked conditions). The second is the possibility of a chunk bias in grammatical exemplars, which is addressed by the BCS and is a principal manipulation in the present design. For these reasons, classifications were compared against chance performance in the main experimental conditions. However, control groups were used in the three-week yoked conditions. Two control groups (one for the BCS condition and one for the non-BCS condition) were used to compare performance in the fully yoked condition (i.e., the rule-search yoked condition). These controls were given only the instruction manipulation and were not provided descriptions or feedback. Controls attempted to classify the same exemplars used by the rule-search group over the 3-week duration (i.e., the exemplars classified the first two weeks and then the letter-switched exemplars the third week), again, without training or feedback.

Participants were taken from the Psychology 201 participant pool. The following method for participant selection was used to control for attrition rates, which are of particular concern in the proposed study due to the time-series design and small number of participants in each experimental group. A brief of the study was posted for

Psychology 201 students on the announcement board on the first floor. The brief described the study as simply "A 3-week Study of Consciousness" to avoid cues to the learning aspects of the study, which may represent a confound for the incidental learning conditions. It then directed those interested to contact the researcher for more information. Those that did were informed that participation in the 3-week study would fulfill the 5-hour research requirement for Psychology 201 (each day of participation lasted about 30-45 minutes, depending on the assigned condition). It was hoped that this process of first reading about the study and then inquiring further would establish a kind of "tacit investment" by the prospective participants that would encourage motivation and successful completion of the study. This, without actually stating that motivation is required, which may represent (additional) bias in the random selection of participants from the 201-subject pool. Despite this effort, a number of participants either did not show up at their scheduled time or failed to successfully complete all three weeks of testing. This resulted in unequal participant numbers in some conditions, but the differences were not enough to adversely affect analyses.

Materials

The AG used in the present study is shown in Figure 3. Training and testing exemplars were balanced for chunk strength and were similar to those used in Knowlton and Squire (1996). Actual exemplars are shown in Appendix A. Twenty-three training exemplars and 16 test exemplars between lengths 2-6 were generated from the AG. Introducing an error in each of the 16 training exemplars created the non-grammatical test strings. The original 16 testing exemplars were used in the non-BSC condition and paired with 16 non-grammatical strings in the 2-AFC testing task. In the BSC condition, the exemplars were constructed such that chunk strength was equal across grammatical and non-grammatical strings. Across all conditions, the16 pairs were presented twice in random order for a total of 32 testing trials. Additionally, the AG selected to create exemplars was, by comparison to other AG options, less complex. The same training and testing exemplars were presented in pseudorandom-order each week (though were switched to a different letterset on the final week), which should have made the learning task easier across all conditions. These last two aspects of the experimental design were employed in an effort to facilitate as much conscious learning as possible, particularly in the rule-search non-BCS condition.

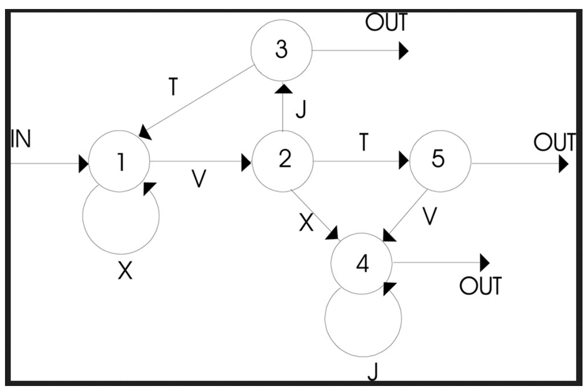

Figure 3. Grammar used by Knowlton and Squire (1996, Exp. 1).

Training and Testing Protocol

The training protocol was as follows. Participants were presented with each training exemplar for 5 s each. Training each week used the same set of training exemplars presented in random order each week. Participants in the familiarization conditions were asked to familiarize themselves with the training exemplars. Rule-search participants were told that the exemplars were rule-governed and that they should attempt to determine the nature of these rules.

Testing began two minutes after training. Exemplars were presented in a 2-AFC test, which presented one grammatical and one non-grammatical string side-by-side in the center of the computer screen for each of 32 testing trials. Participants were not given feedback on their performance, as it has been shown that feedback has little (e.g., Mathews et al., 1989) to no effect (e.g., Dienes, 2005). Feedback may also represent a confound for the incidental learning conditions by implying consequences for 'incorrect' familiarity judgments. After each trial, participants were asked to provide a confidence rating of their judgment (i.e., confidence in their judgment that their selection was either grammatical or familiar) by selecting either 50 (completely guessing), 60, 70, 80, 90, or 100 (complete certainty). The only difference between groups were the directions, the familiarity group was asked to select the exemplar that was most familiar, and the rule-search group was asked to select the string that seemed to follow the grammatical rules most closely. Confidence ratings represent an online training measure and also provide for a comparison of performance over time.

After every 8 classifications, participants saw two different sets of instructions presented on the computer screen. Participants in the rule-search condition were asked to provide instructions for their yoked counterparts, which were written down on a sheet provided to the participants (for a total of 4 different instructions). Participant instructors were asked to describe as completely as possible exactly what they were doing to classify the strings. On each subsequent set of directions, they were asked to provide as much new information as possible. They were also informed that it was important to reference letters and letter sequences as much as possible in their descriptions. The familiarization groups were asked to reflect on the strings that they had found to be familiar for a total 20 s (established based on an estimate of the time it took for instructors in the rule-search groups to record their descriptions).

Yoked participants attempted to classify the exact same testing exemplars as their yoked counterparts. Before classifying the first 8 strings, yoked participants were given the instructions provided by instructors for their first 8 classifications only. Before yoked classification on the next 8 trials, they were given instructions generated from only trials 9-16 by the instructors, etcetera.

All participants were informed of the rule-governed structure used to generate the exemplars immediately before training began in the third and final week. The letter set was changed in the transfer task week from XVJT to BLFM. Participants in the rule-search condition were reminded that in the first two weeks their task was to use some form of strategy to try to learn the rules of the grammar. Participants in the familiarization group were informed for the first time of the complex set of rules used to generate the exemplars and were then asked to provide classification descriptions in the same fashion as the rule-search groups. All participants were told that the letters used in the first two weeks of the experiment were now switched to an entirely new set of letters, but that the exemplars still followed the same set of simple grammatical rules used to generate exemplars throughout the study. Participants were then trained on the new exemplars and informed that they would be asked to select the grammatical string in a 2-AFC task, as before. Participants were provided as much time as necessary to make classifications throughout the study and the next pair was presented after a selection was recorded on the computer keyboard.

All participants were given a PDP string completion task at the end of the final week of testing. The string completion test for the inclusion and exclusion tasks presented two different sets of 16 grammatical exemplars previously used during the *transfer* condition (the letter switch condition). Each string had either one or two letters removed across all positions and replaced by a blank. 16 strings were presented in columns on two sheets of paper, one for the inclusion task and one for the exclusion task. The letters available to fill in the blanks were provided on each sheet along with the description of the task. In the inclusion condition, participants were asked to generate grammatical sequences. In the exclusion task, participants were asked to generate non-grammatical sequences. In both conditions, participants were asked to complete the task by attempting to recall all knowledge that they have acquired during training and testing, including knowledge that they knew that they knew and knowledge that they just felt like they knew. In the inclusion task, the knowledge was used to generate grammatical strings. In the exclusion task, the same knowledge was to be recalled (or sensed) in order to create non-grammatical strings.

Predictions and Analyses

Again, Reber (1989, 1993) has argued that knowledge acquired during an AGL task is both unconscious and not bound to specific perceptual features. However, if perceptual features are what is being represented, they should be accessible declaratively, representing a conscious form of knowledge. These perceptual features should be flexibly applied to new exemplars leading to improvement over the three weeks of training and testing in the non-BCS conditions. This knowledge should also transfer fairly well in the transfer condition if it is not solely bound to the perceptual features of the exemplars. Extended training may also develop unconscious abstract knowledge that facilitates transfer of learning during the third week across all 3-week conditions (Johanson, 2009). As such, subjective measures should detect unconscious knowledge in both instructional conditions, though it should be found at higher levels in the incidental learning conditions. Fragmentary knowledge should be present in all conditions in some form and especially prevalent in the non-BCS conditions due to the availability of chunk information. Performance should improve on explicit tasks (yoked conditions) in the intentional learning conditions. If the increased training leads to more abstract and unconscious representations, transfer performance in the familiarization condition will be better than in the rule-search condition.

Evidence for unconscious knowledge has also been associated with fewer errors during classification as compared to an increased number of errors when knowledge is conscious (Reber, 1989). This is because it is assumed that conscious knowledge is far more flexible and can be applied to a variety of situations, where unconscious knowledge is restricted to a particular simple pattern (Reber, 1989). This should lead to higher performance scores in conditions where unconscious knowledge is being applied (i.e., the incidental learning conditions).

Difference Scores for Zero Correlation and Guessing Criterion

The predictions for both the zero-correlation and guessing criteria are as follows. It is hypothesized that knowledge in the familiarity conditions will be more unconscious than that found in the rule-search conditions due to the instructional manipulation. Knowledge in BCS conditions across conditions should tend to be more unconscious due to the lack of chunk strength information available to make classifications. Alternatively, knowledge in no-BCS conditions should be more conscious due to the availability of chunk information. The incidental BCS condition should show the best classification performance when compared across conditions. The knowledge used to make classifications in this condition is hypothesized to be unconscious due to the incidental learning instructions. Based on this, the guessing criterion should measure high accuracy and guessing, denoting unconscious knowledge based on this criterion. The incidental no-BCS condition should have a similar measure, but may record fewer guesses when grammatical strings are selected because of the availability of chunk information. Whether this will be entirely accessible in the incidental condition is questionable, but some chunk information will likely become conscious to participants. Intentional no-BCS learning conditions should show good grammatical exemplar selection and low guess selection, again displaying the conscious nature of the knowledge acquired in the intentional condition. The BCS intentional condition should show low performance and high guess rates representing a decrease in both conscious and unconscious knowledge acquisition.

Yoked Conditions

Differences between classification performances, which typically show better performance for instructors, should decrease with extended training with 'abstract instructions' becoming more informative to yoked participants. All measures of consciousness in yoked conditions should display a bias toward conscious knowledge, as the only available information will be the instructions provided by the instructors. However, it is possible that yoked participants could learn something on their own during testing (Redington & Chater, 1996). The yoked control conditions are employed to determine if this was the case. Yoked conditions address the important question of whether abstract knowledge can be verbalized. Reber (1989) says "no," Mathews (1997) says "yes." Subjective measures applied to yoked participants addressed this issue. A negative correlation between instructor and yoked subjective measures may be found due to an increase in unconscious knowledge measured in instructors; as unconscious knowledge increases, ability to verbalize would decrease (Reber, 1989) and 'abstract verbalizations' would be less informative.

It was hypothesized that performance for single-week yoked conditions would be poor but statistically above chance. Yoked participant performance in the non-BCS conditions should be better than in the BCS conditions, again due to the availability of chunk information that is accessible to instructors. Single-week yoke participants in the incidental and intentional learning conditions should be similar, with a slight bias toward better performance in intentional learning conditions (once again, due to chunk information). Predictions for subjective measures applied to single-week yoked participant are in line with 3-week yoked participants.

PDP across Conditions

A string-completion-task variation of the PDP measured the proportion of grammatical strings created for the inclusion and exclusion conditions, which were recorded for each experimental condition. According to PDP-logic, if participants have perfect, conscious knowledge of the grammatical strings used during training and testing in the transfer condition, then they should always create grammatical strings in the inclusion condition and never in the exclusion condition. The equations applied to describe performance in each condition were taken from Jacoby et al. (1993, p. 141). The probability of completing a string to create a previously provided exemplar in the inclusion task is the probability of recollection (R) plus the probability of the string coming to mind unintentionally (A) when there is a failure of recollection, A (1-R). This represents a situation where all available knowledge is being applied. The inclusion task can be represented formally as:

$$\text{Inclusion} = R + A(1-R).$$

In the exclusion task, strings are completed to create a previously studied grammatical string only when it is unintentional (i.e., there is no conscious knowledge that the string was presented during training or testing and participants incorrectly provide a grammatical sequence). The exclusion task can be represented formally as:

$$\text{Exclusion} = A(1-R).$$

The probability of consciously remembering previous strings is estimated as the probability of completing strings to create a grammatical string in the inclusion condition minus the probability of creating grammatical strings in the exclusion condition:

$$R = \text{Inclusion} - \text{Exclusion}$$

Once a measure of conscious knowledge is established, the influence of unconscious knowledge can be determined with the following equation:

$$A = \text{Exclusion}/(1\text{-}R)$$

Once measures of conscious and unconscious knowledge are established, each can serve as the dependent measures in analyses. Hypotheses were that the PDP should diagnose differences in inclusion and exclusion tasks as a function of instruction type and BCS. If unconscious knowledge increases, as we would expect in the incidental conditions, then participants should find it more difficult to suppress unconscious influences in the exclusion task, leading to an increase in the use of chunks that make exemplars grammatical. It was hypothesized that inclusion task performance would be good for both instruction groups due to increases in both unconscious and conscious knowledge, but lower in BCS conditions due to the lack of available chunk information. It was expected that intentional learning would be bound more to the physical characteristics of the exemplars, thus more conscious in nature (Dienes, 2008a). Importantly, chunk information was also available in the incidental learning conditions. With this in mind, it was expected that performance in the inclusion task would be similar in the no-BCS conditions; however, in the BCS conditions, participants in the incidental learning conditions may show better performance due to having acquired some tacit knowledge about the underlying structure of the grammar. If this was found to be the case, performance on the exclusion task should reveal an inability to suppress unconscious knowledge leading to the creation of (unintended) grammatical strings. Yoked participant performance on the PDP should suggest that knowledge acquired in these conditions is primarily conscious.

Analyses across all measures followed the same general format. Analysis of the four main experimental groups employed a 2 (BCS v. no-BCS) X 2 (Familiarize v. Rule-Search) X 3 (Time) mixed model ANOVA. To analyze the effects across the rule-search groups and their yoked counterparts, I applied a 2 (BCS v. no-BCS) X 2 (Instructor v. Yoke) X 3 (Time) mixed model ANOVA. A 2 (Instructor v. Yoke) X 2 (Familiarity v. Rule-Search) X 2(BCS v. non-BCS) ANOVA was applied to all group classification performance on the third week.

RESULTS

Classification as a function of type of instruction, BCS, and time.

Classification rates were used as the dependent measure across the instruction, BCS, yoked, transfer (i.e., a switch to a different letter set), and time-series conditions (Table 2). Passive abstraction, accessibility of knowledge, and abstractness of knowledge are all properties of IL that can be tested by this design (Mathews, et al., 1989). Passive abstraction is evidenced by the instruction manipulation if the knowledge acquired is equivalent across passive and intentional conditions. The yoked conditions are used to test the accessibility of knowledge—if yoked performance is lower than their yoked counterparts, knowledge used by the 'instructors' to classify exemplars is not available to be described accurately and is thus considered to be tacit. Abstractness of knowledge is tested in the transfer conditions, finding support if performance levels are maintained despite a switch in the perceptual features of the exemplars (i.e., a change in letter set) on the third week.

The main experimental manipulation of instruction—rule-search/intentional versus familiarity/passive—was used to establish explicit and implicit learning conditions, respectively. The BCS (balanced and non-balanced chunk strength across exemplars presented in the 2-AFC task) manipulation was meant to control for classification bias bound to perceptual features of grammar (bi- and trigram information). It was hypothesized that balancing chunk strength would have a greater affect on the rule-search conditions, as it was assumed that chunks would be the most available form of information to use while actively attempting to consciously decipher the underlying grammatical structure. We will first look at the effect of the two main experimental manipulations of instruction and BCS.

Mean Percent Correct Classifications as a Function of BCS, Instruction,
And Week of Practice of Experimental and Yoked Participants

Condition	Week 1	Week 2	Transfer Week 3
Familiarity BCS			
Experimental	60(11)	58(10)	62(10)
3-week Yoked	--	--	--
1-week Yoked			55(10)
Familiarity no-BCS			
Experimental	62(9)	66(14)	65(13)
3-week Yoked	--	--	--
1-week Yoked			54(10)
Rule-search BCS			
Experimental	60(15)	55(12)	57(12)
3-week Yoked	51(10)	46(12)	53(11)
1-week Yoked	--	--	51(10)
Rule-search no-BCS			
Experimental	61(15)	61(7)	59(11)
3-week Yoked	50(13)	57(12)	54(10)
1-week Yoked	--	--	53(10)
Control 3-week Yoked BCS	51(11)	50(10)	44(16)
Control 3-week Yoked no-BCS	50(3)	53(9)	49(15)
Control 1-week Yoked			50

Table 2. Mean percent of correct classifications as a function of BCS, instructional condition, and week of practice for experimental, three-week yoked, and single-week yoked groups. SD is provided parenthetically.

Effect of Instruction and BCS

Mixed-model analysis with BCS and instruction as the between-subjects factors and week of testing as the within-subjects factor of classification rates across the main experimental conditions revealed a marginally significant main effect of BCS, $F(1,69) = 3.45$, $p = .068$, $\eta_p^2 = .049$, with classification performance being higher in the non-BCS conditions ($M = 68\%$, $SD = 13$) when compared against the BCS conditions ($M = 63\%$, $SD = 11$). All other comparison failed to reach significance. Balancing the chunk strength should have had more of an effect on the rule-search conditions. However, an additional planned comparison suggested that balancing the chunk strength had more of an effect on passive learning group classification performance, $F(1,67) = 3.03$, $p = .087$, $\eta_p^2 = .043$ ($M = 69\%$, $SD = 12$ in the non-BCS condition versus $M = 62\%$, $SD = 9$ in the BCS condition), than on the intentional learning groups, $F(1,67) = .80$, $p = .38$, $\eta_p^2 = .012$ ($M = 63\%$, $SE = 11$ in the non-BCS condition versus $M = 60\%$, $SD = 12$ in the BCS condition), though the effect was marginal. It was also hypothesized that the rule-search groups would outperform familiarity groups, in general. Another planned comparison revealed that performance for each of the instructional groups was fairly equal over the first two weeks; however, the passive instruction groups outperformed the intentional instruction groups on the third week, $F(1,67) = 3.80$, $p = .055$, $\eta_p^2 = .054$ ($M = 63\%$, $SD = 12$ for the passive groups versus $M = 57\%$, $SD = 12$ for the intentional groups).

Taken together, the expected effect of balancing the exemplar chunk strength was realized, however, the passive groups were affected more than the intentional learning groups. This suggests that despite not being instructed to focus on detecting the grammatical rules, the passive instruction groups were relying on the available bi- and trigram information to some extent while developing their superior knowledge of the grammar. The extent to which this knowledge was conscious or unconscious will be considered when we look at the data from the subjective measures.

Passive Abstraction

If classification rates are roughly equivalent across the instruction conditions (and are above chance), then it can be suggested that a degree of tacit knowledge was acquired implicitly in the passive learning conditions. An independent-samples t-test was conducted to compare the classification rates across the instructional conditions. There was no significant difference in the scores for familiarity (*M* = 68%, *SD* =12) and rule-search (*M* = 64%, *SD* = 12%) conditions, $t(69) = -1.49$, p = .14, which was not surprising considering that this has been found repeatedly in past experiments (e.g., Reber, 1976, see Reber, 1989 for a review). Familiarity-instruction groups acquired as much (or more) knowledge of the grammar as did the rule-search groups. Specifically, in accordance with the assumptions of the instruction manipulation, the results suggest that the tacit knowledge that was acquired in the passive instruction groups was roughly equivalent to the knowledge that was acquired in the rule-search groups, which is assumed to be more conscious in nature. However, the conscious nature of the knowledge acquired by the rule-search groups is brought into question when we look at performance from yoked participants.

Accessibility of Knowledge

A mixed-model ANOVA with BCS and Yoke as between-group variables and week of practice as the within-group variable on the rule-search groups and their yoked counterparts (including controls), revealed an interaction between classification scores and BCS, $F(2,204) = 2.97$, $p = .05$, $\eta_p^2 = .03$. Pairwise comparisons revealed that performance of the yoked controls was statically higher in the non-BCS condition (*M = 53%,* SD = 9) than the BCS condition (*M* = 50%, *SD* = 10) during the second week. Neither score was statistically different than zero, so the effect was not remarkable. A between subjects effect also indicated a difference in scores between rule-search groups and their yoked counterparts and controls, $F(2,102) = 11.50$, $p < .001$, $\eta_p^2 = .18$. All other comparisons were non-significant, though a main effect of BCS was again found to be marginal, F (1,102) = 3.14, p = .08, η_p^2 = .03 and in the expected direction (M = 59%, SD = 12 for non-BCS and M = 56%, SD = 11 for BCS). A post hoc Tukey test showed that the rule-search groups differed significantly from both their yoked counterparts (p < .001) and controls (p = .001); however, yoked group performance did not differ significantly from controls. This provides conclusive evidence that the rule-search groups failed to describe accurately to their yoked counterparts the knowledge they were using to make their classifications. The conclusion that can be drawn from these particular findings is that participants in the rule-search conditions did not have conscious knowledge of the information they were using to make their classifications, which suggests that it is unconscious to some degree.

One-sample *t*-tests were conducted to compare classification performance of the controls against a 50% chance rate. There was no significant difference in control classification rates (M = 50%, SD = 8) from chance, $t(29) = -.06$, p = .95. These results suggest performance in BCS and non-BCS conditions under familiarity and rule-search instructions can just as accurately be compared against chance performance. Specifically, no statistically distinguishable tacit knowledge was acquired by the control groups, which if found, would have needed to be considered when accounting for learning in the three-week yoked conditions.

There is, however, an important consideration regarding the accuracy of the descriptions provided. This consideration does not challenge the presence of tacit knowledge in the rule-search conditions, but may account for some of the performance of their yoked counterparts. The accuracy of the information provided to yoked participants is provided in Table 3.

Percent of Correct Information in Description

Condition	Week 1	Week 2	Transfer Week 3
Familiarity BCS	--	--	35
Familiarity no-BCS	--	--	20
Rule-search BCS	30	14	33
Rule-search no-BCS	20	25	33

Table 3. Average amount of correct information in descriptions provided by instructors to their yoked counterparts. Correct information was coded based on accurate references to either bi- or trigrams, or to salient features (i.e., letters at the beginning and end of exemplars).

Correct information was coded based on accurate references to either bi- or trigrams, or to salient features (i.e., letters at the beginning and end of exemplars). This information was then divided by the sum of all such information made available in the descriptions. As can be seen, instructors across all conditions displayed limited abilities to accurately describe relevant information about the grammatical structure. This suggests that their knowledge is more tacit in nature.

A 2 (Instructor v. Yoke) X 2 (Familiarity v. Rule-Search) X 2(BCS v. non-BCS) ANOVA was applied to all group classification performance on the third week. This analysis revealed a main effect for instruction, $F(1,211) = 4.25$, $p = .04$, $\eta_p^2 = .02$ and yoke, $F(3,211) = 8.18$, $p < .001$, $\eta_p^2 = .10$. All other main effects and interactions failed to reach significance. The effect of instruction indicated that the passive instruction groups classified more exemplars correctly than did the rule-search search groups (*M* = 69%, *SD* = 12 versus *M* = 55%, *SD* = 11, respectively). A post hoc Tukey analysis of the yoked conditions showed a significant difference between instructor (*M* = 61%, *SD* = 12) and their one-week yoked counterparts (*M* = 53%, *SD* = 10), again indicating that knowledge used by the instructors to classify exemplars is not available to be explicitly and accurately described, thus unconscious.

Abstractness of Tacit Knowledge

The abstractness of tacit knowledge was tested with a transfer task between the second and third weeks. A mixed-model analysis with BCS and instruction as between-subjects factors and week of testing as the within-subjects factor of classification rates across the main experimental conditions revealed no significant within-group differences across performance during the last two weeks, $F(1,67) = .310$, $p = .58$, $\eta_p^2 = .01$ (second week, M = 60%, SD = 15 and third week, M = 60%, SD = 17). These results indicate that knowledge did transfer to the letter-switch exemplars. Specifically, these results suggest that the knowledge used to classify exemplars during the third week is, to some degree, abstract. However, there were between-group main effects for BCS, $F(1,67) = 5.48$, $p = .02$, $\eta_p^2 = .076$, and instruction, $F(1,67) = 5.10$, $p = .03$, $\eta_p^2 = .071$, which indicated better performance in both the non-BCS conditions and in the incidental learning conditions. The better performance in the non-BCS conditions has been addressed previously and is the expected effect of making bi- and trigram information available to assist classifications. The better performance in the incidental learning conditions may suggest the combined effects of both conscious and unconscious learning. Further evidence for this possibility is revealed in the analyses of data from the subjective measures.

A separate mixed-model analysis with BCS as the between groups factor and Time as the within-groups factor on three-week yoke performance did reveal a within-subjects interaction effect of Session and BCS, $F(1,77) = 4.46$, $p = .04$, $\eta_p^2 = .06$. Classification scores in the non-BCS condition decreased from week two (M = 58%, SD

= 12) to week three (*M* = 54%, *SD* = 11), and the opposite was the case in the BCS condition (*M* =46%, *SD* = 12 and *M* = 53%, *SE* = 11, respectively). Both conditions seem to have transferred knowledge from the second to third week indicating the presents of abstract knowledge. The decreased performance in the non-BCS condition suggests that performance was more directly related to the perceptual features of the exemplars and thus more conscious in nature. Specifically, instructors seem to have been able to transfer some knowledge about the chunks to their yoked counterparts. The increase in performance found in the BCS condition suggests that the knowledge applied in the third week was more abstract and tacit in nature. Performance was, however, not statistically different from chance. It is likely that any knowledge present during the third week in the BCS condition was acquired on that week alone.

The combined results of analyses of the classifications scores suggest that the knowledge used to classify exemplars is to some extent abstract and is acquired implicitly. The results also indicate that the knowledge is largely tacit. These findings are in-line with suggestions that knowledge acquired during an AGL is both unconscious and not bound entirely to specific perceptual features (Reber, 1989, 1993). There is some indication that perceptual features were being learned and were available for description across all conditions, especially in the rule-search non-BCS condition. However, in general, there was little evidence of conscious knowledge indicated by the analysis of yoked performance, which was far lower than was reported by Mathews. It is possible that the additional training provided in that study lead to the increase in explicit knowledge about the underlying grammar. Knowledge across all groups transferred to week three, which provides additional evidence of the abstract representational form and tacit nature of the knowledge found predominantly across groups. We will now move to the analyses of the subjective measures and PDP post-test to determine if their results confirm the general unconscious nature of this knowledge.

Subjective Measures of Consciousness

Subjective measures have been developed to determine if knowledge acquired under AGL conditions is either conscious or unconscious or some combination thereof. The *zero-correlation criterion* tests whether subjective confidence ratings relate to performance. If participants classification rates and confidence ratings relate, it is assumed that their high confidence is due to being aware of the knowledge they are using to make correct classifications. Conversely, if they do not relate, it is assumed that participants are not aware of the knowledge that they are using to make correct classifications and is unconscious. The *Chan Difference Score* is the difference in confidence ratings when correct and incorrect and is one of the dependant measures that can be use to quantify this difference. Within-subjects effects are of particular relevance to the zero-correlation criterion, as a single score taken from each participant may not detect variations in confidence ratings offered throughout testing (Dienes, 2005). If participants are just as confident when they are correct as when they are incorrect, they would receive a score of zero denoting a complete lack of metaknowledge. The *guessing criterion* is the total percentage of correctly classified letter strings while guessing (i.e., participants record a confidence rating of 50%), which used the total number of guesses as the baseline. Higher scores indicate more unconscious knowledge in accordance with this measure. Results of the subjective measures are provided below (Table 4).

Percent Confidence Ratings when Classifying Correctly and Incorrectly, Chan Difference Scores, and Guessing across BCS, Instruction, and Week Performance of Experimental and Yoked Participants

	Chan Difference			Guessing		
Condition	Wk 1	Wk 2	Wk3	Wk 1	Wk 2	Wk 3
Familiarity BCS						
Experimental	2(5)**	3(6)**	2(3)**	66(17)	69(14)	78(24)
3-week Yoked	--	--	--	--	--	--
1-week Yoked	--	--	2(3)*	--	--	68(7)
Familiarity no-BCS						
Experimental	2(2)**	3(3)**	2(3) **	61(16)	73(19)	50(22)
3-week Yoked	--	--	--	--	--	--
1-week Yoked	--	--	2(2) ^{m}	--	--	84(9)
Rule-search BCS						
Experimental	2(3)*	1(3)	1(2)*	75(11)	71(11)	50(15)
3-week Yoked	⦸	⦸	⦸	⦸	⦸	⦸
1-week Yoked	--	--	⦸	--	--	⦸
Rule-search no-BCS						
Experimental	3(4)*	2(3)**	4(4)**	80(17)	70(10)	76(19)
3-week Yoked	⦸	1(2)*	2(2) ^{m}	⦸	79(6)	84(8)
1-week Yoked	--	--	⦸	--	--	⦸
Cont 3-week Y BCS	⦸	⦸	⦸	⦸	⦸	⦸
Cont 3-week Y no-BCS	⦸	⦸	⦸	⦸	⦸	⦸
Cont 1-week						

Table 4. The Chan Difference Score is the difference in average confidence between correct and incorrect classifications. A maximum score of 50 denotes complete metaknowledge and 0 denotes complete tacit knowledge. The Guessing Criterion is the total percentage of correctly classified letter strings while guessing, which uses the total number of guesses as the baseline. Scores range from 50 to a maximum of 100, 50 represents no unconscious knowledge 100 denotes complete unconscious knowledge according to this measure. SD is provided parenthetically. ^{m} = marginally significant ($p < .08$), * = $p < .05$, ** = $p < .01$ Significance indicates presence of metaknowledge according to the zero-correlation criterion and the presence of tacit knowledge according to the guessing criterion. ⦸ = no score due to classification performance failing to be statistically distinguished from chance.

Chan Difference Scores

Mixed-model analysis with BCS and instruction as the between-subjects factors and week of testing as the within-subjects factor on Chan difference scores of the main experimental groups revealed no significant within-subject effects, $F(2,134) = .49$, $p = .61$. *t*-tests were used to compare group performance over the three weeks against zero. The familiarity/BCS group scores were significantly different from zero each week, $t(17) = 3.20$, $p < .01$, $t(17) = 4.00$, $p < .01$, and $t(17) = 2.90$, $p = .01$, respectively. This was also the case for the familiarity/non-BCS group scores each of the three weeks, $t(17) = 3.34$, p

$< .01$, t(17) = 5.69, $p < .01$, and $t(17) = 3.45$, $p < .01$, respectively. Rule-search/BCS scores during the second week were not significantly different from zero, $t(17) = 1.64$, $p = .12$, indicating a lack of metaknowledge, but first and third week performance did differ significantly from zero, $t(17) = 2.57$, $p = .02$ and $t(17) = 2.34$, $p = .03$. Group scores for the rule-search/non-BCS condition each week also were statically distinguished from zero, $t(16) = 2.41$, $p = .03$, $t(16) = 2.88$, $p = .01$, and $t(16) = 3.56$, $p < .01$, respectively. The results suggest that metaknowledge was present across all of the main experimental groups each week, except for the second week in the rule-search/BCS condition. The presence of metaknowledge in main experimental passive learning groups may seem to contradict the assumptions of the instruction manipulation—that passive group knowledge should be predominantly tacit. Equally, the presence of metaknowledge in the third week may seem to contradict an (implied) assumption of the transfer condition—that since knowledge is more abstract in form, it is more unconscious in nature. We will address this in the general discussion.

Yoked performance in the BCS rule-search conditions did not exceed chance level classification performance, so could not be analyzed. The same was true for the 3-week control conditions and first week of performance in the non-BCS condition. A mixed-model ANOVA with Instructor (Instructor v. Yoke) as the between-group variable and week of practice as the within-group variable on the non-BCS rule-search group and their yoked counterparts over the last two weeks revealed no significant within-subjects interaction effects for difference scores and instructor condition, $F(1,40) = 1.80$, $p = .19$. However, there was a between-groups effect of instructor, $F(1,40) = 5.39$, $p = .03$, $\eta_p^2 = .12$, which indicated that instructors ($M = 2.70$, $SE = .50$) possessed more metaknowledge over these two weeks than yokes (*M* = 1.19, *SE* = .41). *t*-tests on the second and third week non-BCS three-week yoke conditions revealed a significant difference from zero the second week, $t(24) = 2.36$, $p = .03$, and a marginally significant difference on the third week, $t(24) = 1.93$, $p = .07$. These were the only three-week yoked groups that indicated any metaknowledge. These findings express the expected affect of BCS on the rule-search instructors. When chunk information was available, the instructions offered to yoke counterparts improved their classification performance to levels above chance. The metaknowledge indicated in these yoked conditions is likely bound to the explicitly described chunk information. The lack of metaknowledge during the first yoked week performance may be due to the instructors' lack of practice in providing descriptions. It could also be due to the unconscious nature of the knowledge acquired by instructors to classify exemplars.

A 2 (Instructor v. Yoke) X 2(BCS v. non-BCS) ANOVA was applied to passive group instructors and their one-week yoked counterparts on third week Chan Difference (again, rule-search groups could not be analyzed due to chance classification performance). No significance was indicated between instruction and BCS, $F(1,76) = .09$, $p = .76$, which suggests that metaknowledge is roughly equivalent across these conditions. *t*-tests were performed only for the passive one-week yoked groups because their classification performance exceeded chance—BCS, $t(17) = 2.15$, $p = .05$ and non-BCS, $t(21) = 1.86$, $p = .077$. No knowledge of the grammar (meta or tacit) was indicated in the rule-search one-week yoked conditions. The indication of tacit knowledge in the passive groups suggests that instructors in these groups were none-the-less able to share some aspects of their knowledge, as well. This was not the case for the rule-search participants, except in the three-week non-BCS yoked condition. However, it is possible the yoked performance across all yoked conditions was due to the yoked participants' own acquisition of tacit knowledge of the grammar. Tacit knowledge in the one-week yoked passive groups may not be as likely due to the lack of practice; thus, it is more likely that their knowledge is more conscious in nature. Specifically, this suggests that the passive yoked groups' metaknowledge is bound to the knowledge they received from instructor descriptions. However, when we consider the accuracy of the descriptions provided by the passive groups instructors in the BCS (35% correct) and non-BCS (20% correct), this may not seem likely. This suggests that the metaknowledge present in this group was acquired, at least in part, by interacting with the exemplars alone.

Guessing Criterion

Mixed-model analysis with BCS and instruction as the between-subjects factors and week of testing as the within-subjects factor on guess rates across the main experimental conditions revealed no significant within- or between-subjects effects. The average group scores for weeks 1-3 were M = 81, SD = 20; M = 68, SD = 11; and M = 72, SD = 21, respectively. This indicated the presence of tacit knowledge in all of the main experimental groups. As to whether the chance level performance of yoked counterparts in the rule-search groups was due, in part, to the tacit nature of instructor knowledge, a 2 (Instruction) X 2 (BCS) ANOVA was performed. This analysis revealed a marginal effect of instruction, $F(1,25) = 3.53$, $p = .07$, $\eta_p^2 = .12$, indicating more tacit knowledge in the rule-search groups (M = 78, SD = 15) than in the passive groups (M = 65, SD = 16). It is thus possible that the poor classification performance in the yoked conditions was due to the tacit nature of the instructor knowledge. The average accuracy of the descriptions offered by the rule-search groups also supports this (*M* = 35%). Analysis of second week scores revealed no significant differences, $F(3,19) = .08$, $p = .97$. Third week analysis similarly showed no significant differences across groups, $F(3,18) = .84$, $p = .49$ (average $M = 74$, $SD = 20$). Tacit knowledge was only marginally indicated in the familiarity no-BCS, $t(14) = 1.92$, $p = .08$, and failed to be indicated in the rule-search BCS condition. The lack of tacit knowledge in these conditions seems to partially contradict the assumptions of the BCS manipulation (more metaknowledge in the non-BCS conditions and more tacit knowledge in the BCS conditions). The Chan difference score for the rule-search BCS group does indicate some metaknowledge, but the poor classification performance of their three- and one-week yoked counterparts ($M = 53$, $SD = 11$ and $M = 51$, $SD = 10$, which failed to be distinguished from chance level performance) suggests that the amount of metaknowledge is low. All knowledge for this group transferred from weeks two ($M = 55$, $SD = 12$) to three ($M = 57$, $SD = 12$), so was abstract in nature according to the assumptions of the transfer condition. It may also be unconscious by the same assumptions, which should have been represented by a higher guessing criterion score. One reason that the guessing criterion failed to recognize this tacit knowledge may be due to the low level of guesses in this condition. There were only two confidence ratings of 50% recorded, one for an incorrect response and one for a correct response. This may be a delimiting factor in the application of this criterion.

A 2 (Instructor v. Yoke) X 2 (BCS v. non-BCS) ANOVA was applied to passive group instructors and their one-week yoked counterparts on the third week guess rates (rule-search groups could not be analyzed due to chance classification performance). No significant differences were found between participant condition and BCS, $F(1,14) =$

3.11, $p = .10$, $\eta_p^2 = .03$. *t*-tests were performed only for the passive one-week yoked groups because their classification performance exceeded chance—BCS, $t(17) = 2.15$, $p = .05$ and non-BCS, $t(21) = 1.86$, $p = .08$. Tacit knowledge was thus indicated in both passive yoked conditions.

A summary of the results of the subjective measures reveal a few interesting trends, each of which only partially coincides with original predictions. It was predicted that knowledge would be more tacit in nature in the passive instruction groups and more conscious in nature in the intentional instruction groups. However, metaknowledge was indicated across all conditions and across all weeks of testing, which when considered in light of performance in the yoked conditions, draws into question the explicit nature of metaknowledge. Tacit knowledge was also indicated across all groups and was especially prevalent in the rule-search non-BCS condition, where it was least expected to be found. It was also predicted that knowledge in the BCS conditions would be more tacit in nature and that metaknowledge would be more prevalent in the non-BCS conditions. Again, this seems to be only partially confirmed by the performance in the passive no-BCS condition. It was predicted that familiarity groups would have the best overall classification performance, yet, the best performance was predicted to be in the familiarity-BCS group, but was eventually indicated in the familiarity no-BCS condition. The suggestion across all findings is that the metaknowledge may be characterized by something other than an explicit understanding of the perceptual features and grammatical structure.

Process Dissociation Procedure

According to PDP-logic, if participants possess perfect metaknowledge of the grammatical structure they will create grammatical strings in the inclusion task and never in the exclusion task. It was predicted that conscious knowledge would be indicated by the inclusion task across all groups due to increases in both conscious and unconscious knowledge of the grammar, but lower in the BCS conditions. It was also predicted that tacit knowledge would be more prevalent in the familiarity and BCS conditions, which should lead to higher scores in the exclusion task. Results for the PDP are provided in Table 5.

Process Dissociation Procedure measures of
Conscious (Inclusion Task) and Unconscious (Exclusion Task) Influences
As a Function of BCS, Instruction, and Yoked Conditions

Condition	Inclusion	Exclusion
Familiarity BCS		
Experimental	.02(.21)	.27(.16)
3-week Yoked	--	--
1-week Yoked	.24(.26)	.16(.13)
Familiarity no-BCS		
Experimental	.04(.13)	.29(.09)
3-week Yoked	--	--
1-week Yoked	.16(.21)	.18(.11)
Rule-search BCS		
Experimental	.09(.14)	.38(.17)
3-week Yoked	.01(.17)	.38(.08)
1-week Yoked	.08(.20)	.21(.08)
Rule-search no-BCS		
Experimental	.21(.28)	.27(.18)
3-week Yoked	.17(.14)	.26(.14)
1-week Yoked	.03(.14)	.21(.13)
Cont 3-week Y BCS	.00(.12)	.19(.14)
Cont 3-week Y no-BCS	.00(.08)	.21(.18)
Cont 1-week Yoked	0	0

Table 5. The Process Dissociation Procedure provides a measure of conscious (C) and unconscious (UC) knowledge of letter sequences that create grammatical strings. Standard errors are provided parenthetically

Mixed-model analysis with BCS (BCS v. non-BCS) and Instruction (Rule-Search v. Familiarity) as the between-subjects factors and Test (inclusion and exclusion) as the within-subjects factors across the main experimental conditions revealed a main effect for type of test, [$F(1,67) = 38.29$, $p < .01$, $\eta_p^2 = .36$] and instruction [$F(1,67) = 9.34$, $p < .01$, $\eta_p^2 = .12$]. BCS failed to reach significance. As shown by a planned comparison on performance in the inclusion task, $F(1,69) = 6.06$, $p = .02$, the rule-search groups possessed more conscious knowledge when compared to the familiarity groups. In-fact, familiarity group performance did not vary significantly from baseline (0 grammatical strings created), $t(35) = 1.07$, $p = .29$, suggesting the almost complete lack of conscious knowledge in accordance with this measure. A planned comparison on performance on the exclusion task indicated that tacit knowledge was statically equal across both instruction conditions, $F(1,69) = 1.43$, $p = .24$. Both groups recorded levels of tacit knowledge that were well above baseline [$t(35) = 10.35$, $p < .01$ and $t(35) = 12.22$, $p < .01$, for rule-search and familiarity groups, respectively]. These results appear to indicate that the acquisition of conscious knowledge was restricted to the rule-search conditions and that both conditions acquired some tacit knowledge of the grammar.

Mixed-model analysis with BCS (BCS v. non-BCS) and Yoke (Instructor v. Yokes) as the between-subjects factors and Test (inclusion and exclusion) as the within-subjects factors across the rule-search groups and their three-week yoked counterparts (excluding controls) revealed an interaction between Test and BCS, $F(1,75) = 17.35$, $p < .05$, $\eta_p^2 = .18$. Pairwise comparisons indicated that there was a statically significant ($p < .01$) difference in test scores for the BCS conditions (inclusion $M = .05$, $SE = .04$, exclusion $M = .38$, $SE = .04$), but only marginal significance ($p = .08$) in the non-BCS conditions (inclusion $M = .19$, $SE = .03$, exclusion $M = .26$, $SE = .02$). The decrease in metaknowledge in the BCS condition is, once again, the expected effect of reducing the availability of chunk information. These results also indicate the prevalence of tacit knowledge across groups, which is in line with the results from the subjective measures.

Mixed-model analysis with BCS (BCS v. non-BCS), Instruction (Rule-search v. Familiarity) and Instructor (Instructors v. Yoke) as the between-subjects factors and Test (inclusion and exclusion) as the within-subjects factors across the main experimental groups and their one-week yoked counterparts revealed two three-way interactions. There was an interaction between Instruction, Instructor, and Test type, $F(1,142) = 7.49$, $p = .01$, $\eta_p^2 = .05$, and one between-subjects interaction between BCS, Instructor, and Test type, $F(1,142) = 3.74$, $p = .06$, $\eta_p^2 = .03$. These three-way interactions were supported only by one two-way interaction between Instructor and Test type. For this reason, I split the data along the Instructor condition and did separate analyses, one on the four instructor conditions and one on their one-week yoked counterparts. The 2 (Rule-search v. Familiarity) X 2 (BCS v. non-BCS) X 2 (Inclusion v. Exclusion) mixed-model analysis across the main experimental groups was performed previously. The results of this analysis are at the beginning of this section. Those results did not indicate any interactions, so it was expected that the same analysis on the one-week yoked groups would reveal an interaction. This was in fact the case with an interaction being found between Instructions and Test type, $F(1,75) = 7.73$, $p = .01$, $\eta_p^2 = .09$. Pairwise comparisons indicated that there was a statistically significant ($p < .01$) difference in test scores for the rule-search conditions (inclusion $M = .05$, $SE = .03$, exclusion $M = .21$, $SE = .01$), but no such difference found in the familiarity groups ($p = .59$; inclusion $M = .20$, $SE = .03$, exclusion $M = .17$, $SE = .02$). These results suggest that familiarity groups had more total knowledge (metaknowledge and tacit knowledge) when classifying exemplars.

This should be evidenced by better classification rates when compared against the rule-search groups. However, analysis of one-week yoke classification performance collapsed across BCS conditions failed to support this, $F(1,78) = .91$, $p = .34$, though scores did seem to suggest this expected effect (rule-search $M = 56\%$, $SD = 12$; familiarity $M = 58\%$, $SD = .12$).

Subjective Measures on the Process Dissociation Procedure

Confidence ratings were recorded for each response on both tests of the PDP. To my knowledge, subjective measures have not been used in such an application. It was predicted that there should be a relationship between the scores used to indicate metaknowledge (the zero-correlation criterion and inclusion task), as well as a relationship between those used to indicate tacit knowledge (the guessing criterion and exclusion task). Table 6 provides the PDP data once again, along with scores from the subjective measures as applied to each of the PDP tests.

PDP Measures of Conscious (Inclusion Task) and Unconscious Influences (Exclusion Task),
Chan Difference Scores on PDP, and Guessing Criterion on PDP
As a Function of BCS, Instruction, and Yoked Conditions

Condition	Inclusion	Exclusion	Chan		Guess	
			Inclusion	Exclusion	Inclusion	Exclusion
Familiarity BCS						
Experimental	.02(.21)	.27(.16)	5(7)	3(7)	53(7)	62(18)
3-week Yoked	--	--	--	--	--	--
1-week Yoked	.24(.26)	.16(.13)	8(7)	3(5)	57(8)	56(7)
Familiarity no-BCS						
Experimental	.04(.13)	.29(.09)	5(5)	2(4)	52(2)	59(11)
3-week Yoked	--	--	--	--	--	--
1-week Yoked	.16(.21)	.18(.11)	3(5)	0(1)	61(11)	64(24)
Rule-search BCS						
Experimental	.09(.14)	.38(.17)	7(8)	3(5)	52(4)	59(20)
3-week Yoked	.01(.17)	.38(.08)	1(1)	0(1)	82(25)	58(10)
1-week Yoked	.08(.20)	.21(.08)	6(9)	3(5)	55(6)	57(7)
Rule-search no-BCS						
Experimental	.21(.28)	.27(.18)	7(7)	1(1)	50(0)	51(2)
3-week Yoked	.17(.14)	.26(.14)	5(8)	5(8)	54(4)	50(0)
1-week Yoked	.03(.14)	.21(.13)	9(12)	4(6)	53(4)	57(6)
Cont 3-wk YBCS	.00(.12)	.19(.14)	⦸	⦸	⦸	⦸
Cont 3-wk Yno-BCS	.00(.08)	.21(.18)	⦸	⦸	⦸	⦸
Cont 1-wk Yoked	0	0	0	0	0	0

Table 6. The Process Dissociation Procedure provides a measure of conscious (inclusion task) and unconscious (exclusion task) knowledge of letter sequences that create grammatical strings. The Chan Difference Score is the difference in average confidence between correct and incorrect classifications. A maximum score of 50 denotes complete metaknowledge and 0 denotes complete tacit knowledge. The Guessing Criterion is the total percentage of correctly classified letter strings while guessing, which uses the total number of guesses as the baseline. Scores range from 50 to a maximum of 100, 50 represents no unconscious knowledge 100 denotes complete unconscious knowledge according to this measure. Standard deviations are provided parenthetically. ⦸ = scores unable to be determined due to chance level performance.

Chan Difference Scores on PDP Inclusion and Exclusion Tests

Mixed-model analysis with BCS and Instruction as the between-subjects factors and Chan difference scores as the within-subjects factors on the PDP inclusion and exclusion tasks across the main experimental conditions revealed an interaction between Chan difference scores and Instructions, $F(1,67) = 4.75$, $p = .03$, $\eta_p^2 = .07$. Pairwise comparisons indicated that Chan difference scores were significantly different in the rule-search conditions ($p < .01$), with scores being higher for the inclusion task ($M = 6.9$, $SE = 1.12$) as compared against scores in the exclusion task ($M = 1.9$, $SE = .81$). This same trend was only marginally significant in the familiarity conditions (p = .08), with scores slightly higher in the inclusion task (M =4.83, SE = 1.10) as compared to scores in the exclusion task (M = 3.01, SE = .79).

Mixed-model analysis with BCS (BCS v. non-BCS) and Yoke (Instructor v. Yokes) as the between-subjects factors and Chan difference scores as the within-subjects factors on the PDP inclusion and exclusion tasks across the rule-search groups and their three-week yoked counterparts (excluding controls because their scores failed to be statistically distinguished from baseline in the inclusion condition) revealed a interaction between Chan difference scores and Yoke, $F(1,75) = 15.55$, $p < .01$, $\eta_p^2 = .17$. Pairwise comparisons indicated that Chan difference scores were significantly different in the instructor conditions ($p < .01$), with scores being higher for the inclusion task (M = 6.9, SE = 1.12) as compared against scores in the exclusion task (M = 1.9, SE = .81). There was no significant difference found in the scores of their yoked counterparts (p = .47), scores for both, the inclusion task (M =3.06, SE = 1.00) and exclusion task (M = 2.51, SE = .65) indicated the presence of metaknowledge. Chan difference scores on the three-week yoked PDP test conditions seem to be overestimating the presence of metaknowledge. This overestimation was far more pronounced in the non-BCS conditions, where we would expect to find more metaknowledge.

Mixed-model analysis with BCS (BCS v. non-BCS), Instruction (Rule-search v. Familiarity) and Instructor (Instructors v. Yoke) as the between-subjects factors and Chan difference scores as the within-subjects factors on the PDP inclusion and exclusion tasks across the main experimental groups and their one-week yoked counterparts revealed no significant within-subjects effects. There was a three-way interaction between

Instructions, BCS, and Yokes, $F(1,142) = 4.92$, $p = .03$, $\eta_p^2 = .03$. Data were split along the Instructor conditions to explore this interaction. The 2 (Rule-search v. Familiarity) X 2 (BCS v. non-BCS) X 2 (Inclusion v. Exclusion) mixed-model analysis across the main experimental groups is located at the beginning of this section. The same analysis on the one-week yoked groups revealed an interaction between Instruction and BCS, $F(1,75) = 7.36$, $p < .01$, $\eta_p^2 = .09$. Pairwise comparisons indicated that Chan difference scores were significantly different in the familiarity conditions ($p = .02$), with scores being lower for the non-BCS conditions ($M = 1.76$, $SE = 1.05$) as compared against scores in the BCS conditions ($M = 5.66$, $SE = 1.16$). There was no significant difference found in the rule-search conditions ($p = .18$), scores for both, the non-BCS conditions ($M = 6.81$, $SE = 1.10$) and BCS conditions ($M = 4.70$, $SE = 1.13$) indicated the presence of metaknowledge. One again, the general trend in the data is to over-estimate the presence of metaknowledge across conditions.

Guessing Criterion on PDP Inclusion and Exclusion Tests

Mixed-model analysis with BCS and Instruction as the between-subjects factors and Guess as the within-subjects factors on the PDP inclusion and exclusion tasks across the main experimental conditions revealed no significant within- or between-subjects effects, [$F(1,26) = .06$, $p = .82$ and $F(1,26) = .19$, $p = .67$, respectively]. High levels of tacit knowledge were indicated across all groups. The trend to overestimate tacit knowledge seems to also be the case with the Guessing criterion across the PDP task conditions.

Mixed-model analysis with BCS (BCS v. non-BCS) and Yoke (Instructor v. Yokes) as the between-subjects factors and Chan difference scores as the within-subjects factors on the PDP inclusion and exclusion tasks across the rule-search groups and their three-week yoked counterparts (excluding controls) revealed an interaction between Guessing scores and Yokes, $F(1,27) = 4.33$, $p = .05$, $\eta_p^2 = .14$. Pairwise comparisons indicated that Guessing scores were significantly different in the yoked conditions ($p = .03$), with scores being higher for the inclusion task ($M = 68.3$, $SE = .04$) as compared against scores in the exclusion task ($M = 53.9$, $SE = .03$). There was no significant difference found in the scores for instructors ($p = .54$), scores for both, the inclusion task ($M = 51.1$, $SE = .04$) and exclusion task ($M = 51.1$, $SE = .03$) indicated the presence of tacit knowledge. The significant difference in the yoked conditions was due to the uncharacteristically high guessing score in the three-week yoke non-BCS condition. Review of the data revealed that when guess rates were very low (rates < 2) participants were guessing correctly most of the time. This does indicate the presence of tacit knowledge, but the very low guess rates may represent a delimiting factor in this application.

Mixed-model analysis with BCS (BCS v. non-BCS), Instruction (Rule-search v. Familiarity) and Instructor (Instructors v. Yoke) as the between-subjects factors and Guessing scores as the within-subjects factors on the PDP inclusion and exclusion tasks across the main experimental groups and their one-week yoked counterparts revealed a single main effect of instruction, $F(1,50) = 4.44$, $p = .04$, $\eta_p^2 = .08$. Scores in the familiarity conditions ($M = 57.9$, $SE = .01$) were higher than those in the rule-search conditions ($M = 54.1$, $SE = .01$). The general tendency to overestimate tactic knowledge across all groups and conditions persisted.

In summary of this section, it was hoped that applying subjective measure to the PDP test would indicate a relationship between measures that shared common diagnostic capabilities. This does not seem to be the case, as both the zero-correlation and guessing criterion consistently overestimated their target knowledge. It is possible that the number of letter strings on each task (N =16) is too low to allow for more accurate measures of the type knowledge that is being applied across testing conditions. Low performance rates on the PDP string-completion tests may also affect the accuracy. In short, subjective measures used in such an application fail to provide any information about the characteristics of the knowledge applied in PDP string-completion tasks.

CONCLUSIONS

The purpose of this study was to examine characteristics of learning and knowledge involved in AGL tasks and the heuristic value of measures used to substantiate the cognitive unconscious. Results indicated convincing support for the implicit acquisition of tacit knowledge that is at least partially abstract in representational form. Metaknowledge was also indicated, suggesting that both forms of knowledge operate in a synergistic fashion under certain conditions. There is some evidence for two distinct learning processes, though implicit learning processes were most strongly indicated. The experimental manipulations, subjective measures, and PDP posttest used to provide evidence for the distinctness of implicit learning and the predominance of tacit knowledge are discussed below.

Passive Abstraction

The effect of manipulating test instructions offers strong evidence for the passive acquisition of knowledge of grammatical structure. The familiarity groups acquired as much or more knowledge of the grammar when compared to rule-search groups. Performance in the rule-search groups, particularly in the light of the generally poor performance of their three-week yoked counterparts, also indicated the passive acquisition of knowledge. The BCS manipulation provided further evidence for implicit learning. The removal of chunk based information failed to discourage the acquisition of knowledge. This was not only the case in the passive learning group, where we would expect less of an effect, but also in the intentional learning group. When we look at the combined effects of these two manipulations across groups, we find that performance is roughly equivalent between conditions designed to discourage as much explicit learning a possible (the familiarity BCS condition) and those designed to encourage explicit learning (the rule-search non-BCS condition). The generally poor performance of the yoked participants in the rule-search non-BCS condition provides perhaps the strongest support for the passive acquisition of knowledge. Under such conditions, instructors should have been able to describe more of the knowledge they were using to classify exemplars, if it was bound to the chunks of information made available. Performance across both non-BCS conditions was generally better than that found in the BCS conditions, so we must assume that the availability of chunks of information was driving these performance improvements. This suggests that learning was bound to the perceptual features of the exemplars but largely inaccessible to consciousness. This consideration brings into question one of the other purposes of this research, which is to characterize the representational form of acquired knowledge.

Representational Form of Knowledge

IL debates have centered on whether knowledge is bound only to the perceptual features of exemplars or is more abstract in nature. Traditionally, representational forms that are bound to perceptual features are considered to be more accessible to conscious knowledge (Shanks and St. John, 1994). However, the results of this study indicate that even though chunk based information was relied upon to some extent, it was largely inaccessible for description. This suggests that at least some of what was learned was abstract in nature. The performance in the transfer task on the third week, also confirms the abstract character of the representational form. This joint contribution of stimulus-specific and abstract knowledge is in line with interpretations from a number of other studies (e.g., Conway & Christiansen, 2006; Manze & Reber, 1997; Mathews et. al, 1989). The results of this study seem to coincide with an abstractionist account of the representational form of knowledge acquired during an AGL task, which do acknowledge the importance of detecting patterns and simple associations upon which more abstract forms of knowledge are based (Reber, 1989a). Hybrid models that have been advanced which include both chunks and some abstract features (e.g., Mathew, et al., 1989), also characterize the knowledge that was acquired and applied by participants in this study. However, abstractionist accounts are typically associated with tacit knowledge (Reber, 1993), which presents an issue when attempting to account for the metaknowledge indicated across most all experimental conditions.

Measures of Conscious and Unconscious Knowledge

The philosophical basis for the use of subjective measures of mental states is established in a hierarchical framework of first- and second-order mental states. First-order states are bound to the initial activation of sensory mechanisms and second-order states are mental states about first-order states. Much of the knowledge indicated in the present study was tacit in nature, however, some metaknowledge was also indicated by the zero-correlation criterion and the PDP inclusion task. The poor performance of the yoked participants across all conditions seems to question the validity of such measures. However, an account for metaknowledge that is not explicit in nature has been provided by distinguishing a difference between *structural* knowledge and *judgment* knowledge (cf Dienes & Berry, 1997; Dienes & Perner, 1999).

Conceptually, the distinction is premised upon the difference between "knowing something" and "knowing some thing." The latter refers to explicit knowledge of the grammatical structure of exemplars, the former is an intuitive sense of the grammaticality. When structural knowledge is found to be largely unconscious, as was the case in this study, judgment knowledge can be either unconscious or conscious in nature (Dienes & Berry, 1997). Conscious judgment knowledge establishes the phenomenological experience of an intuitive sense of the grammatical correctness of an exemplar, much the same way that we understand the correctness of an English sentence. We do not need to describe all the rules of grammar that make a sentence seem grammatical. Unconscious judgment knowledge establishes the phenomenological experience of guessing. In regards to guessing criterion, correct responses offered while guessing elevates the guessing criterion scores, which indicates unconscious knowledge. Yet, this measure does not evidence a lack of metaknowledge, it simply distinguishes the presence of tacit knowledge. The zero-correlation criterion measures the difference between confidence scores when correct and incorrect. Higher confidence when correct and lower confidence when incorrect indicates the presence of some metaknowledge. However, this measure alone does not tell us if the knowledge is due to an understanding of the structure of the grammar or is better understood as an intuitive sense of the underlying grammatical structure. The performance of the yoked participants in this study provides the final piece of evidence to make this distinction. Yoked performance was generally very low across all conditions, which indicates that the conscious knowledge suggested by the zero-correlation and PDP inclusion test is best characterized as conscious judgment knowledge.

Intellectual Merit and Broader Impacts

A number of long-standing and intensely contested debates have persisted in the field of IL. Debates revolve around the nature of the knowledge acquired in tasks traditionally found to involve IL. Lending no small part in the debate has been the reintroduction of the cognitive unconscious to scientific inquiry. Since that time, the study of the cognitive unconscious has met many challenges from academic psychologists, some going so far as to suggest that the concept of a cognitive unconscious has no place in psychology (e.g., St. John & Shanks, 1997; Shanks & St. John, 1994).

Much of the difficulty involved in pursuing a scientific approach to the cognitive unconscious is based on attempts to establish appropriate experimental methods to highlight unconscious processes. Moreover, much of the contention and debate regarding the scientific study of the cognitive unconscious rests on whether unconscious processes are indeed qualitatively distinct entities that produce (or contribute to) distinct behavioral characteristics.

One of the more relevant contributions of the current research was its effort to determine the validity of indirect measures of the cognitive unconscious. As Dienes (2008) has pointed out, the proof of the usefulness of the guessing and zero correlation criteria is in their heuristic value, which "has scarcely been tested" (p. 54). The combined effect of employing subjective measures, the PDP, yoked and transfer conditions, and the instructional and BCS manipulations proved to be a productive approach to addressing both the representational form and consciousness issues central to the IL debate.

This research advances the field of IL and the cognitive unconscious in a number of ways. It provided evidence of the time-course of learning in AGL, which researchers in the field say are badly needed. It also provided a variety of measures of the development of mental representations over training. The approach of including multiple measures of conscious and unconscious knowledge provided the opportunity to determine if such measures were in mutual agreement with theoretical expectations.

A practical broader application of the current research is how best to design teaching and training methods. For example, it has been suggested that a period of passive reflection on material before more intensive learning may lead to better comprehension of material (Reber, 1993). The logic follows that passive interactions with to-be-learned material creates a type of tacit framework that can better receive and make sense of new information. Performance improvements in the incidental learning conditions provided some support for this application. That is, the familiarization process provided for the "passive acquisition" of the structure of the AG, which then provided for the detection of patterns and co-variations in exemplars that seem to fit the structure. In general, our understanding of how the cognitive unconscious operates will aid in creating more effective and efficient learning environments, whether it is the physical aspects of an actual classroom or a computer environment. Another practical benefit of research in the field of IL and the cognitive unconscious is its application to the design of devices to make them more "user-friendly." Technological advancements, in some cases, seem to have outpaced what minds can work with at a functional level. Advances in our understanding of human learning (and memory) will aid in the development of products that enable rather than frustrate human capacities. This final consideration will no doubt prove very useful in a world where human interaction with technology increases with each passing year.

LIST OF REFERENCES

Allen, R., & Reber, A. S. (1989). Very Long Term Memory for Tacit Knowledge. *Cognition, 8,* 175-185.

Baars, B. J. (2002). The Conscious Access Hypothesis: Origins and Recent Evidence. *TRENDS in Cognitive Sciences, 6(1),* 47-52.

Baddeley, A. (1998). Working Memory. *C. R. Acad. Sci. Ser. III 321,* 167-173.

Berry, D. C. (1997). *How Implicit is Implicit Learning?* New York: Oxford University Press.

Boucher, L., & Dienes, Z. (2003). Two Ways of Learning Associations. *Cognitive Science, 27(6),* 807-842.

Brooks, L.R. and Vokey, J.R. (1991) Abstract Analogies and Abstracted Grammars: Comments on Reber (1989) and Mathews et al. (1989). *Journal of Experimental Psychology: General*, 120, 316-323.

Buchner, A., Steffens, M. C., & Rothkegel, R. (1998). On the Role of Fragmentary Knowledge in Sequence Learning. *Quarterly Journal of Experimental Psychology, 51,* 251-281.

Cheesman, J. & Merikle, P. M. (1984). Priming With and Without Awareness. *Perception and Psychophysics, 36,* 387-395.

Cleeremans, A., Destrebecqz, A., & Boyer, M. (1998). Implicit learning: News from the front. *Trends in Cognitive Sciences, 2(10),* 406-416.

Dehaene, S., & Changeux, J. (2011). Experimental and Theoretical Approaches to Conscious Processing. *Neuron, 70(2),* 200-227.

Destrebecqz, A. & Peigneux, P. (2005) Methods for Studying Unconscious Learning. *Progress in Brain Research, 150,* 69-80.

Dienes, Z., Altmann, G. T. M., Kwan, L., & Goode, A. (1995). Unconscious Knowledge of Artificial Grammars is Applied Strategically. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21(5),* 1322-1338.

Dienes, Z., & Berry, D. (1997). Implicit learning: Below the Subjective Threshold. *Psychonomic Bulletin & Review, 4(1),* 3-23.

Dienes, Z., & Perner, J. (1998). A Theory of Implicit Nature of Implicit Learning. In French, R. M. & Cleeremans, A. (Eds.), *Implicit Learning and Consciousness:*

An Empirical, Philosophical, and Computational Consensus in the Making? New York, New York: Psychology Press.

Dienes, Z. (2008a). Subjective Measures of Unconscious Knowledge. *Progress in Brain Research, 168,* 49-64.

Dulany, D. E., Carlson, R. A., & Dewey, G. I. (1984). A case of syntactical learning and judgment: How conscious and how abstract? *Journal of Experimental Psychology: General, 113,* 541-555.

Dulany, D. E., Carlson, R. A., & Dewey, G. I. (1985). On Consciousness in Syntactical Learning and Judgment: A Reply to Reber, Allen, and Regan. *Journal of Experimental Psychology: General, 114,* 25-32.

Erderlyi, M. H. (1986). Experimental Indeterminacies in the Dissociation Paradigm of Subliminal Perception. *Behavioral Brain Science, 9,* 30-31.

Erderlyi, M. H. (2004). Subliminal Perception and Its Cognates: Theory, Indeterminacy, and Time. *Consciousness and Cognition, 13,* 73-91.

Frensch, P. A. (1998). One Concept, Multiple Meanings: On How to Define the Concept of Implicit Learning. In Stadler, M. A. & Frensch, P. A. (Eds), *Handbook of Implicit Learning.* Thousand Oaks, California: SAGE Publications.

Frensch, P. A., & Runger, D. (2003). Implicit Learning. *Current Directions in Psychological Science, 12(1),* p. 13-18.

Greenwald, Anthony G. (1992). New Look 3: Unconscious Cognition Reclaimed. *American Psychologist*, 47(6): 766–79.

Jacoby, L. L. (1991). A Process Dissociation Framework: Separating Automatic from Intentional Uses of Memory. *Memory and Language, 30,* 513-541.

Jacoby, L. L., Lindsay, D. S., & Toth, J. P. (1992). Unconscious Influences Revealed: Attention, Awareness, and Control. *American Psychologist, 47,* 802-809.

Johansson, T. (2009). Strengthening the Case for Stimulus-Specificity in Artificial Grammar Learning. *Experimental Psychology, 56(3),* 188-197.

Knowlton, B. J. & Squire, L. R. (1996). Artificial Grammar Depends on Implicit Acquisition of Both Abstract and Exemplar-Specific Information. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 22,* 169-181.

Lewicki, P., Hill, T., & Czyzewska, M. (1992). Nonconscious Acquisition of Information. *American Psychologist, 47(6),* 796-801.

Lieberman, M. D., Chang, G. Y., Chiao, J., Bookheimer, S. Y., & Knowlton, B. J. (2004). An Event-related fMRI Study of Artificial Grammar Learning in a Balanced Chunk Strength Design. *Journal of Cognitive Neuroscience, 16(3),* 427-438.

Manza, L., & Reber, A. S. (1997). Representing Artificial Grammars: Transfer Across Stimulus Forms and Modalities. In D. C. Berry (Ed.), *How Implicit is Implicit Learning?* (162-194). Oxford University Press Inc., New York.

Mathews, R. C. (1991). The Forgetting Algorithm: How Fragmentary Knowledge of Exemplars Can Abstract Knowledge. *Journal of Experimental Psychology: General, 120(1),* 117-119.

Mathews, R. C., Buss, R. R., Stanley, W. B., Blanchard-Fields, F., Cho, J. R., & Druhan, B. (1989). Role of Implicit and Explicit Processes in Learning from Examples: A Synergistic Effect. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 15,* 1083-1100.

Mathews, R. C. (1997). Is research painting a biased picture of implicit learning? The dangers of methodological purity in scientific debate. Psychonomic Bulletin and Review, 4, 38–42.

McAndrews, M. P. & Moscovitch, M. (1985). Rule-Based and Exemplar-Based Classification in Artificial Grammar Learning. *Memory and Cognition, 13,* 469-75.

Perruchet, P. & Amorim, M. (1992). Conscious Knowledge and Changes in Performance in Sequence Learning: Evidence against Dissociation. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 18(4),* 785-800.

Perruchet, P. & Pacteau, C. (1990). Synthetic Grammar Learning: Implicit Rule Abstraction or Explicit Fragmentary Knowledge. *Journal of Experimental Psychology: General, 119,* 264-75.

Perruchet, P. & Pacton, S. (2006). Implicit Learning and Statistical Learning: One Phenomenon, Two Approaches. *TRENDS in Cognitive Sciences, 10(5),* 233-238.

Perruchet, P. & Peereman, R. (2004). The Exploitation of Distributional Information in Syllable Processing. Journal of Neurolinguistics, 17, 97-119.

Pothos, E. M., (2007). Theories of Artificial Grammar Learning. *Psychological Bulletin, 133(2),* 227-244.

Reber, A. S. (1967). Implicit Learning of Artificial Grammars. *Journal of Verbal Learning and Verbal Behavior, 6,* 855-863.

Reber, A. S. (1969). Transfer of Syntactic Structure in Synthetic Languages. *Journal of Experimental Psychology, 81,* 115-119.

Reber, A. S. (1985). *The Penguin Dictionary of Psychology.* New York: Viking Penguin.

Reber, A. S. (1989). Implicit Learning and Tacit Knowledge. *Journal of Experimental Psychology: General, 118(3),* 219-235.

Reber, A. S. (1989a). Implicit learning and tacit knowledge. *Journal of Experimental Psychology: General*, 118, 219-235.

Reber, A. S. (1993). *Implicit Learning and Tacit Knowledge.* Oxford University Press, New York, New York.

Reber, A. S. (1997). Implicit Ruminations. *Psychonomic Bulletin & Review, 4(1),* 49-55.

Reber, A. S., & Allen, R. (1978). Analogic and Abstraction Strategies in Synthetic Grammar Learning: A Functionalist Interpretation. *Cognition, 6,* 189-221.

Reber, A. S., & Lewis, S. (1977). Implicit Learning: An Analysis of the Form and Structure of a Body of Tacit Knowledge. *Cognition, 5,* 331-361.

Reber, A. S., Kassin, S. M., Lewis, S., & Cantor, G. W. (1980). On the Relationship between Implicit and Explicit Modes in the Learning of a Complex Rule Structure. *Journal of Experimental Psychology: Human Learning and Memory, 6,* 492-502.

Redington, M., & Chater, N. (1996). Transfer in Artificial Grammar Learning: A Reevaluation. *Journal of Experimental Psychology: General, 125(2),* 123-138.

Reingold, E. M., & Merikle, P. M. (1988). Using Direct and Indirect measures to Study Perception and Awareness. *Perception & Psychophysics, 44,* 563-575.

Rosenthal, D. M. (2005). *Consciousness and Mind.* Oxford: Oxford University Press.

Singley, M. K., & Anderson, J. R. (1989). *Transfer of Cognitive Skill.* Cambridge, MA: Harvard University Press.

Seth, A. K., Dienes, Z., Cleeremans, A., Overgaard, M., & Pessoa, L. (2008). Measuring Consciousness: Relating Behavioural and Neurophysiological Approaches.

Trends in Cognitive Sciences, *12*(8), 314-321.

Servan-Schreiber, E. & Anderson, J. R. (1990). Chunking as a Mechanism of Implicit Learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16,* 592-608.

Shanks, D. R., Green, R. E. A., & Kolodny, J. A. (1994). A Critical Examination of the Evidence for Unconscious (Implicit) Learning. In *Attention and Performance XV* (C. Umilta and M. Moscovitch, Eds), p. 837-860. MIT Press, Cambridge, MA.

Shanks, D. R., & St. John, M. F. (1994). Characteristics of Dissociable Human Learning Systems. *Behavioral and Brain Sciences, 17*, 367–447.

Sun, R., Slusarz, P., & Terry, C. (2005). The Interaction of the Explicit and the Implicit in Skill Learning: A Dual-Process Approach. *Psychological Review, 112(1),* 159-192.

Tunney, R. J., & Shanks, D. R. (2003). Subjective Measures of Awareness and Implicit Cognition. *Memory & Cognition, 31(7),* 1060-1071.

Tunney, R. J. (2005). Sources of Confidence Judgments in Implicit Cognition. *Psychonomic Bulletin & Review, 12(2),* 367-373.

Wilkinson, L. & Shanks, D.R. (2004). Intentional control and implicit sequence learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 30,* 354 -369.

Whittlesea, B. W. A., & Dorken, M. D. (1993). Incidentally, Things in General Are Particularly Determined: An Episodic-Processing Account of Implicit Learning. *Journal of Experimental Psychology: General, 122(2),* 227-248.

Whittlesea, B. W. A. (1997). Implicit Learning: Indirect, Not Unconscious. *Psychonomic Bulletin & Review, 4(1),* 63-67.

Ziori, E., & Dienes, Z. (2006). Subjective Measures of Unconscious Knowledge of Concepts. *Mind & Society, 5,* 105-122.

Ziori, E., & Dienes, Z. (2008). How Does Prior Knowledge Affect Implicit and Explicit Concept Learning? *Quarterly Journal of Experimental Psychology, 61,* 601-624.

LIST OF APPENDICES

APPENDIX A: EXAMPLE TRAINING AND TESTING LETTER STRINGS

Training and Test Letter Strings Used in Experiment 1

Training items			
XXVT	VXJJJJ	XXVJ	XXXVTV
XXVXJJ	XVT	VTVJ	XVXJJ
VXJJ	XXXVT	VJTVX	VT
XVJTVJ	VJ	XXXVTV	VJTVXJ
XXVXJ	XVXJJJ	XXVJ	XXXVX
XVX	VJTVTV	VJTVX	VJTXVJ
			XVXJ
			XXXXVX

Test items

Grammatical and high chunk strength	CS	Grammatical and low chunk strength	CS	Nongrammatical and high chunk strength	CS	Nongrammatical and low chunk strength	CS
XXVXJ	10.4	VJTVT	6.0	VJTV	7.0	XXJJ	6.8
XVTV	6.8	VTVJJ	5.1	XXV	12.3	VXJTJ	4.9
VXJ	9.3	VTVJ	5.6	XVXV	10.0	XXVVJJ	6.2
XXVTV	8.0	XVJTVT	6.7	XVXVJ	9.1	JXVT	5.0
XVJTVX	7.4	VTV	5.0	XXVJJJ	7.8	XXTX	2.8
XXVTVJ	7.7	XVTVJ	6.7	XJJ	7.0	TVJ	6.7
VJTXVX	6.8	XVTVJ	6.1	VXVJ	8.2	VXJJX	5.9
VX	12.0	VTVJJ	5.2	XVXT	7.0	VJJXVT	4.9
M	8.6	*M*	5.8	*M*	8.6	*M*	5.4

Note. CS = chunk strength.

(Table reproduced from Knowlton and Squire,1996)

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Dissertation: A Time-Series Analysis of Implicit Learning and Tacit Knowledge and the Heuristic Value of Methods used to Substantiate the Cognitive Unconscious

M.A., Psychology, University of Mississippi, 2011

Thesis: A Study in Texture Segmentation: Investigating the Role of Template Retuning in Perceptual Learning

B.A., Psychology, Saginaw Valley State University, 2003

TEACHING EXPERIENCE

Instructor, 2011- 2013
University of Mississippi
Course: Cognitive Psychology

Instructor, 2006-2008
University of Mississippi
Courses: Cognitive Psychology, General Psychology, Elementary Statistics

Research Assistant, 2005-2014
University of Mississippi
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HONORS

Outstanding Senior Researcher, 2003
Department of Psychology, Saginaw Valley State University

Outstanding Graduate, 2003
Department of Psychology, Saginaw Valley State University

President, Psi Chi Honor Society, 2001-2003
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PUBLICATIONS and PRESENTATIONS

Noguchi, K., & Streeter, K., (2013). Justice in the Natural and the Social Realms of the World: Quantifying Cognitive and Affective Responses to Destructive Events. *Journal of Personality and Social Psychology.* (Revised and Resubmitted).

Streeter, K. & Prins, N., (2008, May). A Study in Texture Segmentation: Investigating the Role of Template Retuning in Perceptual Learning, Poster presented at the Vision Science Society Conference, Sarasota, FL.