# Implicit and Explicit Knowledge after Limited Exposure to Artificial Grammars of Various Complexity

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## Abstract

Research on implicit learning using the artificial grammar learning (AGL) paradigm has traditionally relied on tasks that promote active engagement, such as memorization, repetition, or rule discovery during the exposure phase. This study examined whether limited exposure, devoid of active engagement tasks, enables participants to distinguish between grammatical and ungrammatical sequences in both simple and complex artificial grammars. Participants performed above chance on the grammaticality task across both conditions but appeared to rely on explicit strategies to a greater degree than reported in previous AGL studies. These findings highlight the critical role of exposure conditions and suggest that exposure to letter strings without active engagement may not sufficiently restrict learning to implicit processes.

**Keywords:** implicit learning; artificial grammar; complexity; zero-correlation and guessing criteria

## Introduction

Understanding how individuals acquire knowledge, both consciously and unconsciously, is essential for advancing our comprehension of human cognition. Implicit learning refers to the mental integration of patterns and structures from the environment, without deliberate effort or awareness (Reber, 1967; 1989). This form of learning is fundamental to numerous aspects of daily life, such as language acquisition (Williams & Rebuschat, 2022), motor skills development (Kal et al., 2018; Maxwell et al., 2000), and decision making (Cohn et al., 2013). Unlike explicit learning, which involves intentionally controlled strategies and conscious thought, implicit learning often unfolds effortlessly, contributing to the seamless mastery of complex systems like grammar and syntax (Reber, 2008).

Although implicit learning is studied using a variety of experimental tasks, a common approach is Artificial Grammar Learning (AGL) paradigm. The AGL provides a controlled environment to investigate how individuals unintentionally acquire intricate rules and patterns (Reber, 1967) using sequences created from a finite-state grammar (Figure 1). Finite-state grammars are complex systems with restricted generative abilities (Chomsky, 1957) that can be used to gain insight into how humans process and internalize structured information.

The AGL varies between studies but generally comprises two primary phases: exposure and testing (Williams & Rebuschat, 2022). During the exposure phase, participants are presented with letter strings without being informed of the complex artificial grammar from which they are derived (Reber, 1967; 1989). In the subsequent testing phase, participants engage in a forced-choice grammaticality judgment task, wherein they evaluate letter strings to determine whether they are grammatical or non-grammatical (that is, they do not conform to the learned grammar).

A well-documented finding in AGL research is that participants reliably discriminate between grammatical and ungrammatical sequences at rates exceeding chance, even when the test phase consists of novel grammatical strings (e.g., Forkstam et al., 2006; Lotz & Kinder, 2006; Reber, 1967). However, participants typically fail to accurately verbalize the underlying grammatical rules at the conclusion of the test phase (Knowlton & Squire, 1996; Reber, 1989; Tunney & Altmann, 2001), suggesting that the rules have been implicitly acquired (Reber, 1989). According to this view, participants implicitly abstract both statistical regularities and rule-based patterns embedded within the stimuli in the absence of explicit awareness.

The implicit nature of knowledge acquisition in AGL, however, is a subject of debate (Batterink et al., 2015; Pothos, 2007). Evidence for transfer effects (i.e., applying learned rules to strings consisting of novel letters), once considered indicative of implicit learning, appears to be restricted to overt, simple features of the stimuli, such as chunk repetitions at the initial or final letter positions (Gomez et al., 2000; Tunney & Altmann, 2001). Further, studies employing source attribution methods, where participants specify whether their grammaticality judgments are based on guessing, intuition, memory, or rule knowledge, have demonstrated that explicit processes may play a role alongside implicit ones (Dienes & Scott, 2005). Debriefing sessions also frequently reveal varying levels of participant awareness of artificial grammar or recurring patterns (e.g., Nissen & Bullemer, 1987; Reber & Lewis, 1977), indicating that separate implicit and explicit mechanisms contribute to performance in AGL tasks. Neuroimaging studies further support this dual mechanism view: implicit learning in AGL is mediated by the basal ganglia (Knowlton et al., 2002) while

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explicit learning engages the left dorsolateral prefrontal cortex (Yang & Li, 2012).

The complexity of the grammar itself can influence whether participants rely more on implicit abstraction or explicit rule discovery. Exposure to simple grammars with easily identifiable patterns may lead to explicit learning, as participants can consciously detect and verbalize the rules (Perruchet & Pacteau, 1990). In contrast, complex grammatical systems, characterized by long dependencies, are more efficiently acquired implicitly, as their underlying structure resists easy conscious articulation (Van Den Bos & Poletiek, 2008). Grammar complexity is characterized by topological entropy (TE), a quantitative measure of the growth rate of the number of unique strings of a given length that a grammar generates as the string length approaches infinity (Bollt & Jones, 2000). For example, a simple grammar that *only* permits repetitive sequences such as "ABABAB" has a low TE, as it generates fewer unique patterns. In contrast, a more complex grammar that allows varied sequences like "ABCDEF," "BACDEF," and so on would exhibit a higher TE, reflecting greater structural complexity. Participants generally show greater accuracy in judging grammaticality for simple grammars with low TE compared to complex ones (Schiff & Katan, 2014; Soetens et al, 2004; Stadler, 1992; Van Den Bos & Poletiek, 2008).

Building on these insights, AGL research has sought to disentangle explicit and implicit knowledge components in AGL tasks by controlling factors such as chunk strength—the frequency with which specific chunks of test strings appeared in the acquisition set. Researchers aimed to demonstrate that reducing chunk frequency would encourage participants to rely on unconscious abstraction rather than declarative memory strategies (Kinder & Assmann, 2000; Knowlton & Squire, 1996). This was motivated by findings showing that when high-frequency chunks are present, performance is often driven by explicit recall rather than implicit grammatical learning (Perruchet & Pacteau, 1990).

However, when researchers are overly focused on decreasing the average level of similarity of stimuli in testing and learning sets, they may inadvertently introduce strings with salient surface features that participants can easily identify in the test phase. The inclusion of such novel surface features within the non-grammatical string fragments—such as impermissible onsets, invalid immediate repetitions, or other prohibited bigrams—increase participants' reliance on these features when discriminating grammatical and non-grammatical items, leading to explicit decision-making (Jiménez et al., 2020).

In attempting to disentangle explicit and implicit learning through surface feature manipulation, researchers often overlook the influence of experimental procedures on the nature of the knowledge acquired. Specifically, the conditions under which participants are exposed to grammar can play a crucial role in shaping the type of knowledge that they are developing. For example, a classic exposure phase can include multiple repetitions of each item in the learning set (e.g., Lotz & Kinder, 2006; Reber, 1967), explicit memorization and recall of letter strings (e.g., Forkstam et al., 2006; Knowlton & Squire, 1996; Perruchet & Pacteau, 1990; Reber, 1967, 1976; Reber et al., 1980; Van Den Bos & Poletiek, 2008), or intentional rule discovery (e.g., Buchner, 1994; Manza & Bornstein, 1995; Reber & Allen, 1978). In contrast, Silva et al. (2017) used a passive task during the exposure phase and still found above-chance performance on a subsequent grammaticality judgment test. However, participants were exposed to the grammar over five consecutive days. It is possible that active and/or prolonged engagement with exemplars encourages explicit learning and interfere with unconscious abstraction.

Similarly, it is common for participants to be informed at the test phase that the letter strings they will encounter were created using complex rules and that they should judge the grammaticality of items based on these rules (e.g., Gomez & Schvaneveldt; Hendricks et al., 2013). This explicit instruction may interfere with the extraction of implicit knowledge developed during training by prompting participants to rely on conscious rule-based reasoning and rule-seeking strategies, rather than implicit learning processes (Buchner, 1994; Manza and Bornstein, 1995, Newell and Bright, 2001).

The robustness of implicit learning effects observed in AGL studies remain uncertain when the aforementioned confounding factors of the experimental design are eliminated. It is also unclear whether more complex grammars can be learned implicitly under limited exposure. This study will investigate if eliminating active engagement with exposure strings (such as memorization, repetition, or search for rules) will result in above-chance performance on an AGL task via predominant use of implicit knowledge.

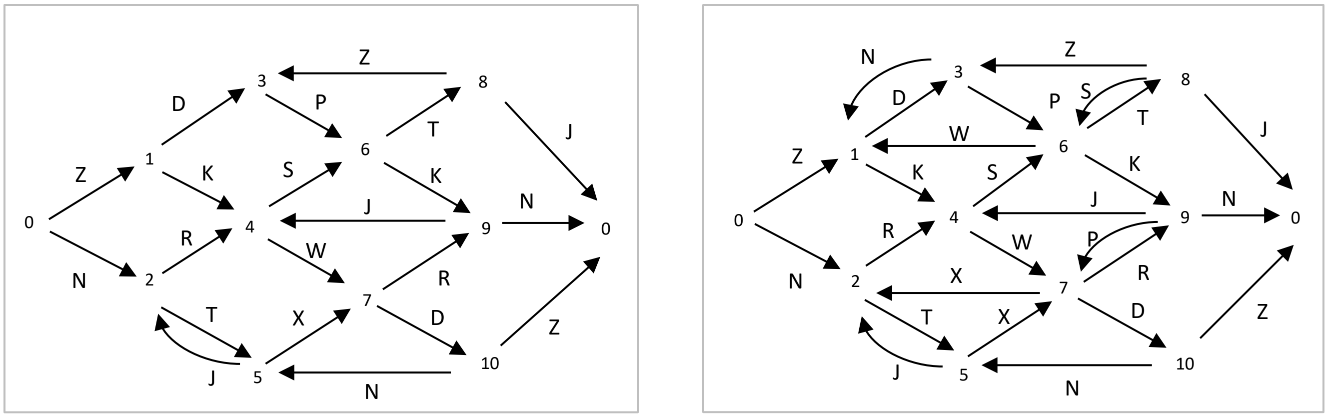
# Methods

## Participants

Sixty-four undergraduate students from Texas Tech University participated in the study to partially fulfill the requirements for a psychology course. The sample size was determined based on prior literature (Van Den Bos & Poletiek, 2008; Batterink et al., 2015) examining artificial grammar learning tasks. Given this sample size, we expected a statistical power of 0.80 to detect a medium effect. The study was approved by the Institutional Review Board before data collection began.

## Materials

Two grammars of varying complexity (Figures 1 and 2) were used in this experiment, adapted from Van den Bos and Poletiek (2008). The complexity of each grammar was assessed using three criteria: grammar topological entropy (TE; Bollt & Jones, 2000), the number of rules, and the number of preceding elements necessary to predict the next element (e.g., Cohen et al., 1990). Exposure sets consisting of 105 and 150 words were created for simple and complex grammars, respectively, with the total number of words



Number of rules: 21
Topological entropy: 0.60
Number of elements to predict next: 3
Word example: ZDPTJ
Ungrammatical word example: ZDTPJ

Number of rules: 47
Topological entropy: 0.85
Number of elements to predict next: 4
Word example: ZDNKSTSKN
Ungrammatical word example: ZDNSKTSKN

Figure 1. Simple (left) and complex grammars used in the study and their characteristics.

constrained by the limitations of the grammar. To minimize participants' reliance on surface features, 50 words were randomly selected without replacement during the learning phase of the experiment. The stimulus sets were balanced, with high-salience stimuli excluded to mitigate biases related to chunk familiarity.

## Procedure

In this study, we employed a retyping task as the primary learning method, designed to reduce the cognitive demands associated with memorization, recall, or rule identification. To address other potential confounding factors, the experimental design eliminated extensive training sessions and explicit statements regarding grammaticality.

**Exposure Phase.** The experiment was conducted online on Qualtrics (https://www.qualtrics.com). Participants were randomly assigned to either a complex (N = 32) or simple (N = 32) artificial grammar complexity group. Both groups were first introduced to an alien named Lumi and told they would see messages in an alien language. They were not informed of any rules used to construct the language. All participants were asked to retype 50 unique strings (for example, ZDPTJ). All letter strings were presented in capitalized letters and participants were instructed to retype them in lowercase while they remained on screen to prevent copying-and-pasting. For each condition, we excluded participants who did not complete the training phase with 70% accuracy or did not complete the task as directed. Although this threshold may appear low for a copying task, it was chosen to accommodate minor typing errors that commonly occur in unsupervised, online experiments. These errors included typos and missed letters.

**Test Phase.** Immediately following the exposure phase, participants completed a surprise grammaticality judgement task with 25 grammatical and 25 non-grammatical strings, none of which they had encountered in the exposure phase. Non-grammatical strings were created by switching two adjacent letters of a grammatical string, excluding the first and last letters. Participants determined whether each word belonged to the alien language encountered during exposure using a 6-point Likert scale ranging from "definitely does not belong to the alien language" to "definitely belongs to the alien language." Following all 50 judgments, participants completed a questionnaire to assess both implicit and explicit knowledge of the grammar. Participants selected whether they based their answers on a guess, intuition, memory of some strings or fragments, or knowledge of the grammar rule. Finally, participants were informed that the strings were compiled according to some rules and were asked to describe any grammar rules they identified. The whole experiment took approximately 20 minutes.

# Results

## Accuracy and Discriminability

We sought to identify if participants would demonstrate above-chance learning on the grammaticality task for both simple and complex grammar conditions after limited exposure. Likert-scale responses were first transformed into binary accuracy scores based on the direction of the response relative to the item's true grammatical status. Specifically, if participants rated a grammatical item as more likely to be from the alien language (i.e., > 3) or a nongrammatical item as less likely (i.e., < 4), the response was scored as accurate (1); all other responses were scored as inaccurate (0). Thus, accuracy reflects whether participants made a correct categorical judgment, regardless of confidence. Table 1 presents accuracy (the percentage of correct responses) categorized by grammaticality and condition. A mixed-design ANOVA examined the effects of grammar complexity (simple vs. complex) and grammaticality (grammatical vs. nongrammatical) on response accuracy. Across grammars, participants were significantly more accurate for grammatical items (*M* = 0.60) compared to nongrammatical items (*M* = 0.45), *F*(1, 62) = 11.38, *p* < .001, partial $\eta^2$ = .135. This was equally true for both groups; grammar complexity and grammaticality did not significantly interact. Participants in both grammar groups performed above chance (50%) on the test overall (*Msimple* = 0.54, *t*(31) = 3.33, *p* = .002, Cohen's *d* = 0.6; *Mcomplex* = 0.54, *t*(31) = 2.98, p = .005, Cohen's *d* = 0.5). Notably, though, ungrammatical trials did not show above-chance performance for either the simple (*Msimple* = 0.42, t(63) = -2.75, *p* = .996) or complex grammar (*Mcomplex* = 0.48, t(63) = -0.69, *p* =.753).

Table 1. Mean Accuracy (SD) by Grammaticality and Condition for Each Group (Simple and Complex).

| | Simple | Complex |
|---|---|---|
| Grammatical | 0.61 (0.21) | 0.58 (0.20) |
| Nongrammatical | 0.42 (0.21) | 0.48 (0.23) |

To assess discriminability, *d'* was calculated using the proportion of grammatical items correctly identified as such (hit rate) and the proportion of non-grammatical items incorrectly classified as grammatical (false alarm rate) using binary accuracy scores converted previously. The results revealed evidence of discriminability in both the simple grammar condition, *d'* (*M* = 0.16), *t*(37) = 2.67, *p* = 0.011, and complex grammar condition, *d'* (*M* = 0.17), *t*(33) = 2.14, *p* = 0.039. The number of hits in both the simple and complex grammar conditions was notably higher than the number of false alarms, indicating that participants were able to successfully differentiate between grammatical and nongrammatical items. No difference was found between complex and simple grammars, *t*(62.36) = 0.132, *p* = .895).

## Post-experimental Questionnaire

Consistent with prior studies, questionnaire responses collected after the experiment were examined to evaluate the nature of acquired knowledge, where response options "intuition" and "guess" should be associated with implicit learning, and "memory" and "rule" should be associated with explicit learning (see Table 3). There was no evidence that participants showed a statistically significant preference toward any particular response option for both simple ($\chi^2$(3, *N* = 32) = 6.25, p = .100) and complex ($\chi^2$(3, *N* = 32) = 3.75, p = .290) conditions. Furthermore, participants were equally accurate on the grammaticality task regardless of their reported strategy, *F*(3,60) = 1.07, *p* = .369.

When asked to identify any rules they had noticed, some participants mentioned specific letters that appeared in the stimuli. However, none of the participants were able to articulate any meaningful associations or patterns involving these letters, suggesting weak or absent explicit knowledge.

Table 3. Post-experimental Questionnaire Response Percentages and Group Accuracy for Simple and Complex Grammars Combined.

| | Response Percentages | Accuracy |
|---|---|---|
| Intuition | 35.9 | 0.56 |
| Guess | 18.8 | 0.53 |
| Memory | 32.8 | 0.52 |
| Rule | 12.5 | 0.55 |

## Confidence Ratings

Although it is common to ask participants to reflect on their strategies after completing an artificial grammar learning task, researchers have argued that such free verbal reports can be unreliable sources of information (Ziori & Dienes, 2006). To more accurately determine whether knowledge is implicitly acquired, we applied guessing criteria (Dienes et al., 1995), which examines the relationship between participants' confidence levels and the accuracy of their responses. According to this criterion, if individuals report guessing but still perform above chance, they are likely to be relying on implicit knowledge. In contrast, conscious or explicit knowledge is characterized by the ability to distinguish between knowing and guessing, demonstrated by a main effect of confidence on accuracy.

To assess this, the six-point Likert scale data were summarized into three confidence level groups: high ("definitely belongs/does not belong to the alien language"), medium ("most likely belongs/does not belong to the alien language"), and low ("probably belongs/does not belong to the alien language"). Table 2 presents accuracy rates corresponding to each. One sample t-test conducted on low-confidence trials showed that accuracy was not above chance for participants either in the simple (*M* = 0.52, *t*(30), *p* = .561) or complex condition (*M* = 0.49, *t*(30) = -1.24, *p* = .226).

A 2x3 mixed ANOVA with Greenhouse-Geisser correction was used with grammar condition (simple or complex) as the between-subjects variable and confidence (low, medium, or high) as the within-subject variable, which revealed a marginally significant interaction (*F* (1.88, 97.74) = 3.13, *p* = .051, partial $\eta^2$ = .041)[1]. Pairwise t-tests indicated that the interaction was driven by a significant difference between low and high confidence trials for the complex group (*t*(52) = -3.86, *p* < .001), which was absent for the simple group (*t*(52) = -0.58, *p* = 0.83). This indicates that while neither group met the guessing criterion for implicit knowledge (as accuracy on low-confidence trials did not exceed chance), the simple group also failed to show improved performance on high-confidence trials which is an expected marker of explicit knowledge.

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[1] Participants who made zero selections at any confidence level were removed from the dataset (*n* = 10).

Table 2. Mean Accuracy Rates for Low, Medium, and High Levels of Confidence.

| | Simple | Complex |
|---|---|---|
| Low confidence | 0.52 | 0.49 |
| Medium confidence | 0.56 | 0.53 |
| High confidence | 0.53 | 0.59 |

## Discussion

Exposure task types and their influence on learning outcomes are often overlooked in the design of artificial grammar learning experiments. This study sought to investigate whether AGL could be successfully replicated under limited exposure, without incorporating active tasks or stimuli that encourage explicit learning of string fragments.

### Accuracy After Limited Exposure

Participants distinguished between rule-conforming (grammatical) and rule-violating (ungrammatical) items at rates significantly above chance, as evidenced by both accuracy and discriminability scores. However, this effect was primarily driven by high endorsement rates for grammatical items, rather than rejection of ungrammatical items. Performance on ungrammatical trials did not reach statistical significance for either group.

This result replicates the findings of Van Den Bos and Poletiek (2008) using the same grammar structures. Ungrammatical trials with second-order violations—where participants must consider dependencies involving two prior elements—did not exceed chance levels in either work. In contrast, other AGL studies have reported above-chance performance on ungrammatical items (e.g., *M* = 59% in Knowlton & Squire, 1996; *M* = 56% in Christiansen et al., 2010). The discrepancy may be attributed to grammar complexity, as the grammars used in those studies were simpler than the simple grammar tested in the current study.

The tendency for participants in both groups to endorse grammatical strings more frequently aligns with prior findings, which have shown that participants are generally more accurate at identifying and accepting grammatical sequences compared to rejecting ungrammatical ones (Christiansen et al., 2010; Knowlton & Squire, 1996; Meulemans & Van der Linden, 1997). Gillis et al. (2022) proposed that AGL functions as a category learning task, where exposure to grammatical strings helps learners form implicit knowledge of the category but leaves category boundaries unclear. Therefore, it is easier to identify strings that belong to the formed category rather than accurately reject borderline or ungrammatical items.

Under limited active engagement, the mean proportion of correct responses was lower in the current study than is typically reported in AGL experiments (e.g., Van Den Bos & Poletiek, 2008; see Stadler & Frensch, 1998, for reviews). These findings, combined with the observed preference for grammatical strings, suggest that the integrative processes underpinning implicit learning—where participants extract and combine structural information from exposure items—may not have been fully employed. Notably, this outcome occurred even though the number of unique exposure stimuli used in our study was consistent with previous research.

We did not find any AGL studies that used a similar exposure phase design. It is worth noting that while several studies have employed retyping tasks during the exposure phase (Forkstam et al., 2008; Reali et al., 2005), they required participants to retype sequences from memory without visual access to the original strings, often incorporating multiple repetitions or extended exposure periods. Such studies typically report above-chance performance similar to the studies using multi-day exposure phases (Forkstam et al., 2006; Uddén et al., 2008). The above-mentioned findings highlight that robust learning outcomes occur when learners engage actively and repeatedly with exemplars. Such approaches may engage attention and working memory to a greater degree than the paradigm reported here.

Limited active engagement does not always lead to decreased performance on AGL tasks. For example, dual-task exposure AGL studies have shown that the addition of a secondary task does not impair implicit learning, even when attentional resources are divided between tasks (Dienes & Scott, 2005; Hendricks et al., 2013). In our study, however, the lack of active engagement was associated with relatively reduced accuracy. This low performance aligns with findings from other paradigms, such as statistical learning (Toro et al., 2005; Buchner, 1994; Manza & Bornstein, 1995; Reber & Allen, 1978). Further research is needed to better understand these dynamics and the role of attentional engagement in AGL learning processes.

### Sensitivity to Grammar Complexity

Contrary to prior research suggesting that increased grammar complexity, measured through TE, hinders learning in AGL tasks (Schiff & Katan, 2014; Van Den Bos & Poletiek, 2008), the present study found no significant effect of grammar system complexity on learning outcomes. This discrepancy may be attributed to the lack of active exposure phase requiring working memory resources, which resulted in overall low accuracy rates across both simple and complex grammar conditions.

The absence of a complexity effect in our findings raises important questions about the conditions under which grammar complexity influences learning. It is possible that the abbreviated exposure phase in our study created a floor effect, where the overall difficulty of the task overshadowed any additional challenges posed by increased complexity. In such cases, participants may have struggled equally with both simple and complex structures, resulting in comparable accuracy rates. Importantly, though, both groups exhibited evidence of learning.

### The Nature of Acquired Knowledge

Post-experimental questionnaires revealed no evidence that participants had explicit knowledge of the rules underlying either complex or simple grammar. However, the nature of participants' knowledge following limited exposure may not be entirely implicit, especially for the complex grammar, as guessing criteria were not satisfied. First, classification accuracy did not exceed chance when responses were made with low confidence, and this differed significantly from high-confidence responses. This suggests that complex grammar participants relied to some extent on explicit strategies when making grammaticality judgments after limited exposure (Dienes & Scott, 2005). This result diverges from the findings of Van Den Bos and Poletiek (2008), who observed above-chance accuracy for low-confidence responses under exposure conditions involving recall tasks. Interestingly, their study also showed that under a rule-searching exposure condition — which was viewed as an explicit instruction task — participants did not perform above chance on low-confidence trials. The parallels between our findings and those from the rule-searching condition imply that the limited exposure retyping task used in this study may have elicited explicit processing strategies for complex grammar, akin to those observed in explicit rule-searching tasks. In the absence of other instruction, we cannot rule out the possibility that participants spontaneously searched for rules during the typing task. Interestingly, this does not seem to be the case for the simple condition.

In the simple condition, accuracy for low-confidence responses did not significantly exceed chance, but nor did it differ across confidence levels, potentially reflecting a floor effect due to the limited exposure to grammar rules. These findings contrast with previous research that utilized a prolonged active engagement task: There, simple grammars—rather than complex—were more likely to be acquired explicitly due to the simplicity of their structure (Perruchet & Pacteau, 1990).

In sum, these findings suggest that participants' knowledge of an artificial grammar following limited exposure may align with an "explicit-implicit continuum" framework (Reber et al., 1985), where learning outcomes are neither fully implicit nor entirely explicit. A plausible explanation for these findings is that limited exposure may not provide sufficient opportunity for participants to internalize implicit grammatical rules or access implicit processing mechanisms. In studies where memorization tasks are used or offline time is provided between exposure and testing phases (e.g., Mirković & Gaskell, 2016; Nieuwenhuis et al., 2013), participants may consolidate implicit knowledge. In contrast, the absence of such consolidation time in the current study may have prompted participants to adopt a rule-searching approach during testing, particularly for complex grammar items.

## Conclusion

This study examined learning outcomes under limited exposure conditions in an AGL paradigm. Results indicated that participants distinguished between grammatical and ungrammatical strings at above-chance levels, albeit just barely so. Implicit knowledge was evident, especially for the simple grammar group, while some contributions of explicit knowledge were additionally detected within the complex grammar group.

The findings highlight the importance of exposure task design in fostering implicit learning. Limited exposure to grammar, achieved with the retyping task, may not have sufficiently activated the cognitive mechanisms necessary for implicit abstraction of complex grammatical patterns, and/or properly suppressed explicit strategies. Instead, participants appeared to adopt explicit processing strategies, particularly when faced with complex grammar stimuli. The use of such strategies, however, did not lead to better performance. Instead, a predominant reliance on implicit strategies under the current task conditions was equally effective.

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