# Modality transfer of acquired structural regularities:

# A preference for an acoustic route

**Christian Forkstam [a,b,c] (christian.forkstam@mpi.nl)**
**Andreas Jansson [b] (andy@kth.se)**
**Martin Ingvar [b] (martin.ingvar@ki.se)**
**Karl Magnus Petersson [a,b,c,d] (karl-magnus.petersson@mpi.nl)**

**a** Max Planck Institute for Psycholinguistics, Nijmegen, Netherlands; **b** Cognitive Neurophysiology Research Group, Stockholm Brain Institute, Karolinska Institute, Stockholm, Sweden; **c** Donders Institute for Brain, Cognition and Behaviour: Centre for Cognitive Neuroimaging, Radboud University Nijmegen, Netherlands; **d** Cognitive Neuroscience Research Group, Universidade do Algarve, Faro, Portugal

**Abstract**

In this paper we investigate a modality transfer in syntactic classification of an implicitly acquired grammatical sequence structure. Participants either practiced on acoustically presented syllable sequences or visually presented consonant letter sequences. During classification, statistical frequency-based and rule-based characteristics of the classification stimuli were manipulated in an independent manner. Participants performed reliably above chance on the post-acquisition classification task although more so for the group practicing on syllable sequences. These subjects were also the only group to keep a significant performance level also in the transfer condition. The results points to the importance for keeping in mind the ecological validity of the input signal when using artificial grammar learning as a laboratory model for language acquisition.

**Keywords:** Artificial grammar learning; Implicit learning; Modality transfer

## Introduction

Humans possess adaptive mechanisms capable of implicitly extracting structural information solely from observation (Stadler & Frensch, 1998). This extraction typically occurs by means of learning processes that are implicit to theindividual. Implicit learning has several characteristics and are typically compared with and separated from explicit learning. Implicit learning is commonly supposed to have (1) no or limited conscious awareness/access to the acquired knowledge, (2) the acquired knowledge is more complex than simple associations or exemplar-specific frequency-counts, it is (3) an incidental consequence of information processing, and it (4) does not rely on declarative memory (Forkstam & Petersson, 2005; Seger, 1994). Reber (1967) suggested that humans can learn artificial grammars implicitly by an abstraction process intrinsic to natural language acquisition. Recently, there has been renewed interest in using the artificial grammar learning paradigm to model aspects of language acquisition (Gomez & Gerken, 1999) and for exploring differences between human and animal learning relevant to the faculty of language (Hauser et al., 2002).

Natural language acquisition is a largely spontaneous, non-supervised, and self-organized process, where the structural aspects of natural language typically are acquired at an early age largely without explicit feedback (Jackendoff, 2002). Similarly, implicit learning at play in artificial grammar learning is a process whereby a complex, rule-governed knowledge base is acquired largely independent of awareness of both the process and product of acquisition. Other aspects of natural language acquisition, such as reading and writing, are on the contrary examples of typically explicitly taught cognitive skills which require a long period of acquisition. Such a visual/acoustic modality transfer has the potential to function in the artificial grammar learning model in the same way as the distinction over reading/listening in the language function.

In the current study we investigated modality transfer over the visual/acoustic signal in implicit artificial grammar learning. In specific we manipulated the order of acquisition and transfer modality: Participants practiced for 5 days on either acoustically presented syllable sequences or visually presented consonant letter sequences after which they performed a classification test in the same modality, followed by a between modality transfer test. An implicit acquisition paradigm without feedback was used in which the participants were only exposed to positive examples (i.e., well-formed consonant strings) generated by the Reber grammar (**Figure 1**). The classification strings were balanced for substring familiarity relative the acquisition string-set, independent of grammatical status. We attempted to keep the similarity over modality tight by presenting the stimuli in a sequential fashion, both the acoustically presented syllables and the visually presented consonant letter strings. The acquisition sessions were constructed as a repeated short-term memory tasks extending over 5 days, as prolonged acquisition over several days has shown still increasing performance in artificial grammar learning (for acoustic, see Faísca, Bramão, Forkstam, Reis, & Petersson, 2007; for visual, see Forkstam, Elwér, Ingvar, & Petersson, 2008). The subjects were never informed before or during the acquisition about the underlying structure in the acquisition strings. This procedure was used in the attempt to minimize the influence of explicit knowledge and explicit strategies during acquisition. First after the last acquisition session on day 5 were the subjects informed about the existence of the grammatical structure in the acquisition input. They were then instructed to perform grammaticality classifications on new strings similar to the acquisition strings. Two grammaticality classification tests then followed, first in the same modality as during acquisition followed by a transfer test in the transfer modality.

Our choice of visual and acoustic stimuli was made to keep the different modalities within the scope of familiar orthographic as well as acoustic stimuli for the Swedish subjects included in the study, namely the written consonants ({M,S,V,R,X}) and the spoken syllables ({bå, fe, lu, pa, ti}). We chose these alphabets not to make the transfer between the different modality only a matter of written or spoken representation of the same underlying linguistic content, but intended instead to force the transfer not be completely interpreted as a acoustic representation of the written consonants or vice versa.

## Implicit statistical learning and grammar learning

Reber (1967) defined implicit learning as the process by which an individual comes to respond appropriately to the statistical structure inherent in the input. Thus, he argued, the capacity for generalization that the participants show in grammaticality classification is based on the implicit acquisition of structural regularities reflected in the input sample.

However, alternative theoretical frameworks have questioned the abstract ('rule') acquisition interpretation and instead suggest that grammaticality classification utilizes exemplar-based (Vokey & Brooks, 1992) or, alternatively, are based on chunk (n-gram) representations (Perruchet & Pacteau, 1991). Thus, grammar learning, whether natural or artificial, is commonly conceptualized either in terms of structure-based ('rule') acquisition mechanisms or statistical learning mechanisms. Some aspects of natural language (e.g., syntax) are open to an analysis within the classical framework of cognitive science, which suggests that isomorphic models of cognition can be found within the framework of Church-Turing computability (Davis, Sigal, & Weyuker, 1994). These language models typically allow for unlimited concatenation recursion supposedly characteristic for human performance.

Alternative views on artificial grammar learning, that is placed somewhere between the two more common conceptualizations in terms of a rule-based acquisition or a statistical fragment (surface) based learning mechanism, relates the acquisition of simple structured representations as akin to lexical learning which might be supported by statistical learning mechanisms. These representations are then activated, by for example an input string, and actively represented and integrated in working memory during parsing. The latter process is dependent on general integrative mechanisms in the left inferior frontal cortex, and is further dependent during automaticity of this integration process on the head of the caudate nucleus (for a review, see Forkstam & Petersson, 2005).

Support for the implicit character of artificial grammar learning comes for example from lesion studies on amnesic patients. Knowlton and Squire (1996) investigated amnesic patients and normal controls on a classical and a transfer version of the artificial grammar learning task. The patients and their normal controls performed similarly on both artificial grammar learning tasks while the amnesic patients showed no explicit recollection of whole-item or fragment information (i.e., bi- or tri-gram, or so called Associative Chunk Strength, ACS). Based on the results from the transfer version they argued that artificial grammar learning depends on the implicit acquisition of both abstract and exemplar-specific information. Knowlton and Squire (1996) suggested that the latter indicates that distributional information of local sequential regularities is acquired, while the former suggests that abstract (i.e., 'rule-based') representations are also acquired.

It has been argued that sensitivity to the level of ACS is a reflection of a statistical fragment-based learning mechanism while sensitivity to grammaticality status independent of ACS is related to a structure-based acquisition mechanism (Knowlton & Squire, 1996; Meulemans & Van der Linden, 1997). Consequently, it has been argued that sensitivity to ACS reflects an explicit declarative learning mechanism while sensitivity to grammaticality status independent of ACS reflects an implicit procedural learning mechanism (cf. e.g., Petersson, Forkstam, & Ingvar, 2004). It is however well possible to imagine a parallel grammaticality and substring familiarity information acquisition that are in both cases implicit in the sense of independent of conscious awareness during acquisition as well as retrieval.

## Transfer in artificial grammar learning

Few studies on transfer artificial grammar learning report strong cross-modality transfer effects (for a review, see Redington & Chater, 1996). Altmann, Dienes & Goode (1995) and Bigand, Perruchet & Boyer (1998) showed successful transfer from musical tones to letters sequences, and Altmann and colleagues (1995) found also successful transfer from acoustical syllables to graphic symbols as well as from graphical symbols to written syllables (see also Tunney & Altmann, 1999, 2001). Conway & Christiansen have shown that there is an advantage learning an artificial grammar in the auditory modality as opposed to the visual (see e.g. 2005; 2006). In the study of Gomez and Gerken (1999) it was demonstrated that infants can show some transfer capacity, suggesting abstracting capacities beyond the acquisition input. Most studies reporting successful transfer using the artificial grammar learning paradigm have been working within the visual modality and in specific with letter sequences (Gomez & Schvaneveldt, 1994; Reber, 1969). Transfer over letter alphabet has also successfully shown lasting effects of transfer in amnesic patients (Knowlton & Squire, 1996). Within transfer investigation in the acoustic modality have also shown successful performance in 8-month-old infants in the transfer from linguistic to non-linguistic input (Malmberg, 2004).

## The Reber grammar

Formal grammars such as the one used in this study serve as an intentional definition of languages. These represent the formal specification of mechanism(s) that generate various types of structural regularities. They are relevant as a description tool for the processing regularities which are ongoing in any cognitive domain which engages processes operating on structured representations: action planning, language, perception/generation of musical sound patterns, etc. (Petersson et al., 2004). A formal grammar represents a specification of a finite generating/recognizing mechanism for a particular language (e.g., Davis et al., 1994). The transition graph representation of the Reber machine (**Figure 1**) is a representation of the generating and recognition mechanism for the Reber language used in this study.

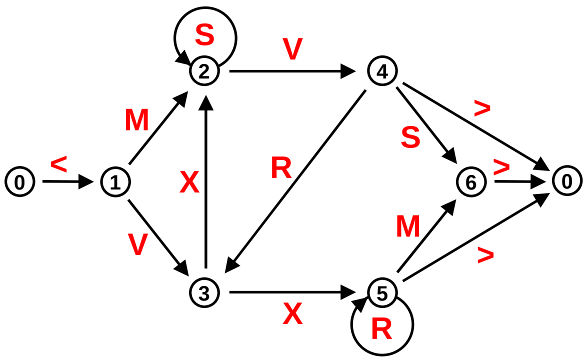


**Figure 1**: The Reber grammar is an example of a right-linear phrase structure grammar which can be implemented in a finite-state architecture, here represented by its transition graph. Grammatical strings are generated by traversing the transition graph from state 0 through the internal states along the indicated direction until reaching an end state. The grammar will e.g. generate/parse <MSSVRXSV> as a grammatical string but not the non-grammatical string <MXSVRXVV>.

## Methods

### Participants

25 right-handed healthy university students fluent in Swedish volunteered to participate in the study (14 females, mean age = 26 years, range = 20-36 years). They were all pre-screened for medication use, history of drug abuse, head trauma, neurological or psychiatric illness, and family history of neurological or psychiatric illness. Written informed consent was obtained according to the Declaration of Helsinki and the local medical ethics committee approved the study. Eleven of the participants were included in the syllable group while 14 participants were included in the consonant letter group due to technical issues.

### Stimulus Material

Grammatical strings with a string length of 5-12 were generated from the Reber grammar. The frequency distribution of bi- and trigrams (2 and 3 letter chunks) for both terminal and whole string positions were calculated for each string in order to derive the associative chunk strength (ACS) for each item (cf., Meulemans & Van der Linden, 1997). An acquisition set was selected as well as 3 sets of grammatical and non-grammatical classification test strings. The non-grammatical strings were generated by a switch of letters in two non terminal positions in a grammatical string. The classification set was further divided into high and low ACS items relative the acquisition string set. We thus manipulated two independent stimulus factors with respect to the 3 classification set, grammaticality (grammatical/non-grammatical) and substring familiarity relative the acquisition string set (high/low ACS) in a 2x2 factorial experimental design.

### Experimental design

The strings presented in a sequential fashion for both the acoustically presented syllables and the visually presented consonant letter strings during acquisition as well as classification. The sequences presented in the acoustic modality were generated from a set of normally occuring syllables in Swedish (i.e., {bå, fe, lu, pa, ti}) while the visual presented sequences were generated from a consonant letter alphabet (i.e., {M, S, V, R, X}). The sequences were presented in a sequential order 300 ms on 300 ms off in both modalities using the Presentation software (nbs.neuro-bs.com). Before the first acquisition session, and in the same modality as during acquisition, did the participants perform a baseline preference classification where they indicated if they liked a string or not based on their immediate intuitive impression (i.e., guessing based on “gut feeling”, see e.g. Forkstam et al., 2008).

During each acquisition phase for each of the 5 days were the participants engaged in repeated short-term memory task without performance feedback. The trials were presented in a sequential fashion with pairs of either syllable sequences or consonant letter strings. The subjects had to respond immediately after presentation indicating whether the sequences were the same or different. Each trial followed each other in a self-paced manner to assure that the subject stayed alert on each trial.

After the last acquisition session on day 5 were the subjects informed that a complex system of rules had been used to generate the acquisition strings, but they were not informed about the rules themselves. They were then instructed to classify novel strings as grammatical or non-grammatical based on their immediate intuitive impression (i.e., guessing based on ‘‘gut feeling’’). They were told that these new strings were all generated from the same system of rules as the acquisition strings. This first grammaticality classification test was performed in the same modality as during acquisition and was immediately followed by a second grammaticality classification performed in the transfer modality. All 3 classification tests distributed to the subjects were always novel to the given subject, and balanced for order over subjects. This means in specific that the underlying regularity for a given grammatical (or non-grammatical) sequence was never reused in another test occasion.

### Data analysis

Mixed-effect repeated measures ANOVAs were used for the analysis of the classification performance using the statistical analysis software R (www.r-project.org). Two measures were used to analyze the subject response, d-prime over grammaticality where hit = grammatical string classified as grammatical, and d-prime over ACS where hit = high ACS string classified as grammatical. For each analysis we modeled the main factors classification session [same/different modality] and group [acoustic/visual] as fixed-effects, and subjects as random-effect. An overall significance level of $P < 0.05$ was used for statistical inference, and explanatory investigations for significant effects were restricted to the reduced ANOVA contrasted over the appropriate factor levels.

## Results

### Classification Performance

**The syllable group** showed significant grammaticality sensitivity in the syllable classification (85% performance level; $F(1, 10) = 137$, $P < 0.001$) and managed to transfer into the visual modality (62%; $F(1, 10) = 19$, $P = 0.001$; **Figure 2 & 3**). A static substring familiarity sensitivity (i.e., ACS) persisted throughout acquisition from the baseline preference classification ($F(1, 9) = 6.2$, $P = 0.032$) to the last day grammaticality classification ($F(1, 10) = 15$, $P < 0.003$) but then disappeared in the transfer modality classification ($P > 0.25$; **Figure 4**).

**The consonant letter group** showed significant grammaticality sensitivity in the consonant classification (68% performance level; $F(1, 13) = 25$, $P = 0.001$) but failed to transfer into the acoustic modality (52%; $P > 0.19$; **Figure 2 & 3**). A static substring familiarity sensitivity (ACS) persisted throughout transfer from the post-acquisition classification ($F(1, 13) = 60$, $P < 0.001$) to the acoustic modality transfer classification ($F(1, 13) = 23$, $P < 0.001$; **Figure 4**).

**Between group effects** persisted for grammaticality sensitivity where the syllable group performed better on the post-acquisition test ($F(1, 22) = 20$, $P < 0.001$) and also in the transfer modality ($F(1, 22) = 10$, $P = 0.004$), indicating a persisting transfer effect for the syllable group as opposed to the random performance of the consonant group (**Figure 3)**. No difference between group in substring familiarity sensitivity (ACS) transfer was found ($P > 0.08$; **Figure 4**).

### Acquisition Performance

Both the group that practiced on syllables and the group that practiced on consonant letters showed an increase in their acquisition performance over the 5 days of the experiment (Day 1 vs. Day 5: $F(1, 22) = 11$, $P < 0.003$; **Figure 5**).

The group that practiced on consonant strings showed significant correlations between their acquisition performance on day 2, 3 and 4 with their transfer performance (d-prime over grammaticality); Spearman's correlation coefficient: Day 2-4 > 0.69, $P < 0.01$). No other correlation between acquisition and classification performance was significant in any of the groups.

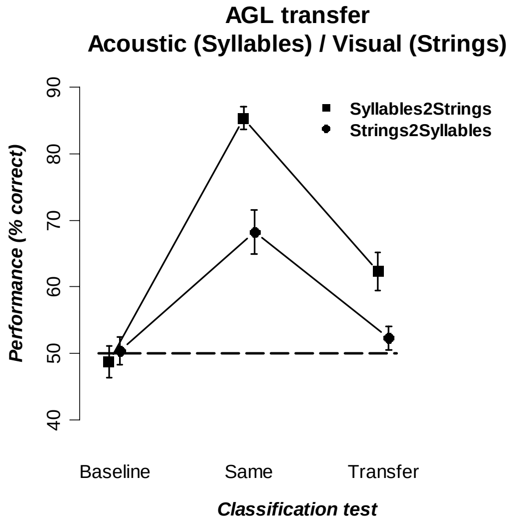


**Figure 2**: Percent correct data for the syllable and consonant string group. Error bars correspond to the standard error of the mean.

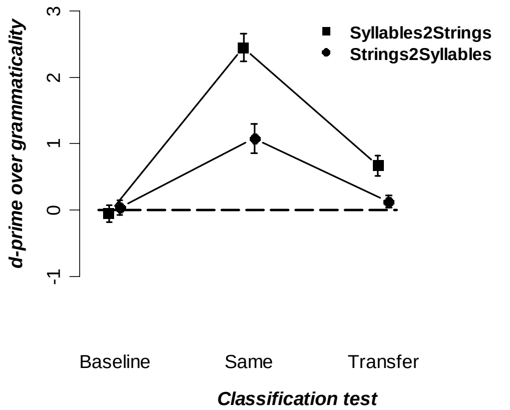


**Figure 3**: D-prime as a function of grammaticality status for the syllable and consonant string group. Hit = grammatical string classified as grammatical.

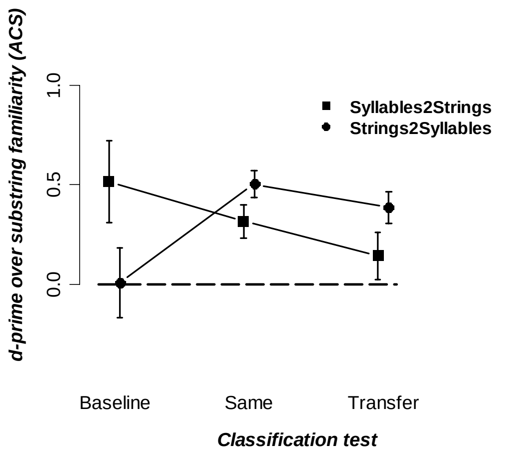


**Figure 4**: D-prime as a function of substring familiarity (ACS) status for the syllable and consonant string group. Hit = high ACS string classified as grammatical.

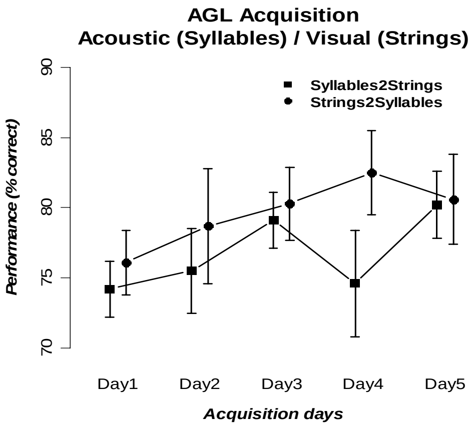


**Figure 5**: Acquisition performance data (percent correct) for the syllable and consonant string group.

## Discussion

In the present study we employed the implicit artificial grammar learning paradigm to investigate the difference in the lasting effects of a modality transfer in artificial grammar learning over the acoustic/visual signal. Results showed that learning was higher overall for sound/syllable sequences, and that transfer only occurred from syllables to strings, and not vice-versa. In grammaticality classification, after 5 days of implicit acquisition, did both subjects who had practiced on acoustically presented syllables and subjects which had practiced on visually presented consonant letter strings classify with high accuracy (**Figure 2**). However, when tested in cross-modality did only those participants which had acquired the acoustical syllable sequences (somewhat equivalent to the listening signal in the language function) show any transfer performance when tested on orthographical letter sequences (equivalent to the reading signal) derived from the same grammar, and not vice versa. This finding is in line with some other studies that also have shown an advantage learning an artificial grammar in the auditory modality as opposed to the visual (see e.g. Conway & Christiansen, 2005, 2006).

In relation to the substring familiarity manipulation in the classification material, did both groups show an effect at the time of the grammaticality classification that was performed in the same modality. In the transfer modality however, the group that had practiced on visually presented letter strings transferred this sensitivity to the acoustic domain, while the other group, which had practiced on acoustic stimuli, did not. This might indicate that when the initial input signal is in the visual domain, the subject is promoted to use substring information, and that this will then be used as cue information when going to the transfer modality, while the opposite route is less affected by such frequency based transfer. Thus, even though no significant difference in substring familiarity reliance in the transfer test was found between groups, a second finding in this study is that even though learning was higher overall for the sound/syllable learning than for the visual/consonant string learning, transfer of substring familiarity only occurred from strings to syllables, and not vice-versa. A general concern in the interpretation of these results is the issue of unit size. Subjects in the auditory modality were always trained on whole syllables, whereas subjects in the visual modality were always trained on consonants. If it is the case individual letters carry with them less information than do syllables, unit size might be confounded in the experimental setup. Auditory to visual might then be easier, just as going from a larger to smaller unit might be easier.

The group that practiced on consonant strings showed a correlation between the acquisition tests on day 2-4 and the transfer test. This finding, that only the group working on sequential input in the visual domain and not the group working on acoustic sequential input, might just be a reflection of a difference in working memory load between the different acquisition tasks. We are more used to sequence information in the acoustic than in the visual domain. Furthermore, because the task is being performed on linguistic stimuli (phonemes presented acoustically and letters presented visually) it might be natural to recode the visual sequence into an auditory code (saying or thinking about the sound of the letter after they see it).

This finding and that only the syllable-to-string group showed transfer performance greater than chance suggests an importance of an ecological validity in the input signal in the use of artificial grammar learning as a laboratory model for language acquisition. The current results point to that in certain situation acoustic stimuli might be preferable over visual stimuli in artificial grammar learning experiments. The idea of an ecological importance in the input signal is in line with the thought that humans are evolved and developed to process auditory/acoustic sequential information more efficiently than visual/orthographic sequential information (see e.g., Conway & Christiansen, 2008, for a similar reasoning). This might merely be due to differences in exposure to different domains (speech vs. writing), and/or that spoken language is likely an evolved human cognitive function while writing is a human invention.

In summary, this paper tries to address important issues about learning, knowledge representation, and language acquisition. It gives some directions to what information that is transferred across the acoustic and visual domain, and leaves a flavor for future investigations in how this finding relates to other kinds of skilled behaviour such as aspects of language learning (speech vs. writing).

## Conclusion

Subjects practicing on acoustical syllables as well as subjects practicing on visual consonant letter strings showed high performance levels after 5 days of implicit acquisition. In cross-modality tests did however only participants that previously were working on syllables show successful transfer performance, while participants that had been working on letter sequences did not. We also found indication of the opposite behaviour for substring familiarity information. The results points to the relevance of an ecological validity of the input signal in the artificial grammar learning model as well as in language learning paradigms at large.

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