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Separate influences in learning: evidence from artificial grammar learning with traumatic brain injury patients

Emmanuel M. Pothos & Rodger L. Wood
Department of Psychology
Swansea University

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Research Report

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Please address correspondence regarding this article to Emmanuel Pothos or Rodger Wood, Department of Psychology, Swansea University, Swansea SA2 8PP, UK. Electronic mail may be sent to e.m.pothos@swansea.ac.uk or R.L.Wood@Swansea.ac.uk

Abstract

Artificial grammar learning (AGL) is one of the most extensively employed paradigms for the study of learning. Grammaticality is one of the most common ways to index performance in AGL. However, there is still extensive debate on whether there is a distinct psychological process which can lead to grammaticality knowledge. An application of the COVIS model of categorization in AGL suggests that grammaticality might arise from a hypothesis-testing system (when grammaticality is appropriately balanced with other knowledge influences), so that prefrontal cortex damage should be associated with impaired grammaticality and intact chunk strength performance. This prediction was confirmed in a study of traumatic brain injury (TBI) patients and matched controls. The TBI patient cohort had diffuse prefrontal cortex damage as evidenced by the history of their injury, CT scans, and severe executive functioning problems. Our results allow a novel interpretation of grammaticality and AGL in general.

Section: 7. Cognitive and Behavioral Neuroscience

Keywords: learning, categorization, COVIS, AGL, traumatic brain injury

1. **Introduction**

In a typical artificial grammar learning (AGL) experiment participants first observe a set of training items and then they are asked to classify new items as consistent or inconsistent with the training items. The test items could relate to the training ones in many ways. For example, the training items and some of the test items obey the rules of the same finite state language (grammatical, G items versus nongrammatical, NG items), or some test items are more similar to the training items than others. AGL has been widely employed to investigate many important hypotheses about human learning, for example, relating to rules, similarity, or associative learning (Berry & Dienes, 1993; Reber, 1993). Accordingly, findings from AGL have had an impact into areas of cognitive psychology where such hypotheses have been purported, such as language, decision making, categorization, and learning in general (Pothos, 2005, 2007).

Two of the most common ways to measure AGL performance are grammaticality and chunk strength. Grammaticality refers to compliance with the finite state grammar employed to generate the training stimuli. Chunk strength reflects whether a test item is composed of parts which have been frequently encountered in the training phase and is generally thought to correspond to similarity. The associative chunk strength of bigrams (symbol pairs) and trigrams (symbol triplets) in the test part is their frequency of occurrence in training (Knowlton & Squire, 1994, 1996; cf. Gomez, 2002). The chunk strength of a test item is the average of the associative chunk strength of all its chunks. In other words, chunk strength is a measure of whether a test item is composed of parts which are familiar from training. How to compute grammaticality and chunk strength from structural properties of AGL stimuli has been a highly researched issue (e.g., Tunney & Altmann, 2001).

Is there a distinct psychological process leading to grammaticality knowledge? This has been a highly controversial issue and a satisfactory answer has been elusive. We stress that the answer will depend on how grammaticality is balanced with other putative knowledge influences (such as chunk strength). It may well be the case that this question is meaningless where appropriate balancing has not been carried out.

We adopt the perspective of COVIS (COmpetition between Verbal and Implicit Systems; Ashby et al., 1998; Zeithamova & Maddox, 2006), which assumes a number of distinct learning systems, principally on the basis of neuroscience data. Of interest here, is a hypothesis-testing system and an information integration/ procedural-based system. The key neural structures for the procedural learning system are the inferotemporal cortex and the tail of the caudate nucleus. It is suggested that this system depends on a dopaminergic reward signal from the ventral tegmental area. The procedural learning system learns to associate a category response with a region of perceptual space without deriving any explicit rule. Note that in early visual areas object information is organized retinotopically, but in later visual areas organization is based on similarity (Op de Beeck et al., 2008). The hypothesis-testing system involves the prefrontal cortex, the anterior cingulate cortex, and the head of the caudate nucleus. The role of the hypothesis testing system is to identify explicit verbal rules which can describe the training instances. The prefrontal cortex (probably better: the dorsolateral prefrontal cortex) has been widely implicated in planning, differentiating amongst conflicting goals, and identifying expectations based on actions (Banich, in press). Moreover, evidence from the Stroop task, suggests that the dorsolateral prefrontal cortex helps sustain an attentional set in the presence of salient distractors (Banich et al., 2000). Accordingly, the dorsolateral prefrontal cortex is a likely candidate for the development of hypotheses for how some training instances could be described. The anterior cingulate cortex is generally associated with error monitoring and conflict resolution (it is implicated in the Stroop task as well). Therefore, it is a likely candidate for an area involved in assessing the validity of different rules.

How could we map the COVIS systems to AGL? A skeptic might point out that COVIS is a model of category learning, so that any hypothesis testing would occur in the learning phase. By contrast, AGL is often considered to involve passive learning (passive observation of the training stimuli), so that hypothesis testing in AGL might take place in test. These considerations might suggest that COVIS does apply in AGL. There are a number of ways to address this problem. First, there is quite a lot of evidence that all learning in AGL takes place in training and not in test (this has been shown, for example, by AGL procedures in which there are two testing blocks; cf. Pothos et al., 2006; Redington & Chater, 1996). Accordingly, AGL can be broadly understood as a categorization task. Second, the knowledge acquired in training has been argued to be a product of a diverse range of processes. Some researchers argue that it is implicit (Reber, 1993). Implicit knowledge would clearly be more consistent with a passive mode of learning. However, other researchers have proposed that, in training, participants develop explicit ‘tests’ (microrules) to describe the regularities in the training items (e.g., Dulany et al., 1984; Mathews et al., 1989). The development of such microrules, almost by definition, would constitute a hypothesis-testing procedure.

So what is the most valid way to characterize learning in AGL? This is still a controversial issue and part of the objective of this work is to help make related progress. We next provide a more specific, preliminary hypothesis for how COVIS could be used to understand AGL performance, assuming it applies in AGL at all (in other words, assuming that AGL performance can have dissociable components which broadly correspond to the ones in COVIS). We would expect that the procedural system possibly learns similarity/chunk strength information about the training stimuli, since chunk strength information is (assumed to be) developed in a passive way. It is based on perceptual similarity and familiarity and it is not informed by any particular hypotheses of the training stimuli. When grammaticality and chunk strength are balanced, then grammaticality plausibly involves knowledge which is more rule-like and less frequency-dependent. For example, knowledge along the lines 'G items can start with an M', is both rule-like (it can correspond to a verbal rule) and its validity can be independent of frequency of observation (cf. Dulany et al.'s, 1984, microrules; cf. Pothos, 2005; Rips & Sloman, 1998). Therefore, under such circumstances (when chunk strength and grammaticality are balanced), the hypothesis testing system can be hypothesized to lead to grammaticality knowledge.

Given the above preliminary hypothesis, a straightforward prediction emerges: with participants for whom the hypothesis-testing system is impaired, we would expect impaired grammaticality and intact chunk strength performance. One potential group of participants is patients who exhibit a range of executive deficits after traumatic brain injury (TBI). TBI is typically acquired as the result of falls or traffic accidents and predominantly implicates prefrontal cortex structures of the brain (Bigler, 2001; Taber et al., 2006). Accordingly, TBI often has little effect on measured intellectual ability or long term memory (Burgess, 2000), yet results in impaired executive functions, characterized by poor decision making and difficulty in planning and organizing daily activities (Wood 2001; Baddeley, 2002). Note that other AGL researchers have employed patient populations, but never before has a TBI sample been used in the context of AGL or the implicit-explicit distinction (Knowlton

& Squire, 1994, 1996; Smith & McDowall, 2005, 2006). Also, note that results from Minda et al. (2008) support the conclusion that a deficit in the prefrontal cortex impairs the function of the hypothesis-testing system. In Minda et al.'s study, children were impaired, relative to adults, in a categorization task which required the explicit development of complex rules, a finding which was explained in terms of the fact that the prefrontal cortex develops later than other areas.

Summing up, the application of COVIS in AGL leads to a general hypothesis (that AGL involves dissociable components) and a more specific one (that knowledge of grammaticality is developed through a hypothesis-testing system, when grammaticality and chunk strength are balanced). Regarding the former, there is some encouraging related evidence. Chang and Knowlton (2004) found that articulatory suppression during training had a larger effect on chunk strength, compared to grammaticality, so that intact attention is required for chunk strength, but not grammaticality. However, this conclusion is complicated by the simple finite state language employed, which may have encouraged participants to adopt heuristics for forming chunks. Moreover, manipulating grammaticality and chunk strength orthogonally typically leads to independent effects for the two (e.g., Knowlton & Squire, 1994, 1996). Similar results have been reported when comparing grammaticality and chunk strength using multiple regression analyses (Johnstone & Shanks, 1999; Pothos and Bailey, 2000—though note that Pothos & Bailey employed stimuli other than letter strings, cf. Conway & Christiansen, 2006). Finally, Lieberman et al. (2004; cf. Fletcher et al., 1999; Skosnik et al., 2002) found that chunk strength performance was linked to medial temporal lobe activation, whereas grammaticality to right caudate nucleus activation, with corresponding activations negatively correlated. Such results motivate a search for separate learning processes for grammaticality and chunk strength.

Note that Friederici and colleagues have explored artificial grammars in a series of experiments, with a view to understand language processing (e.g., Friederici et al., 2006; Opitz & Friederici, 2003, 2004). For example, Opitz and Friederici (2003) reported that improved performance in an artificial language led to increased activation of the left inferior frontal gyrus (Broca's area) and decreased activation in the left hippocampal area. Some caution is needed before extrapolating such conclusions to AGL. For example, in the work of Friederici and colleagues there is a specific attempt to simulate real-language learning. This is achieved through extensive intentional training, corrective feedback, and manipulating a 'syntax' factor with a similarity one through superficial changes in the perceptual form of the stimuli. By contrast, in AGL training is incidental, limited (typically one or two presentations for the training items), no corrective feedback is provided, and grammaticality is manipulated against similarity at the structural level of the stimuli.

2. Results

Four participants in the control group were eliminated because they responded with a 'yes' for all test items, leaving 27 participants in the control condition and 19 TBI patients.

For each participant we computed two indices of performance. A grammaticality index was computed as the proportion of the G test items that were endorsed and the proportion of NG items which were rejected (the two proportions were averaged). A chunk strength performance index was computed as the proportion of endorsed high chunk strength items and rejected low chunk strength ones. Table 1 presents summary results for the two performance indices for controls and TBI patients. Note that both performance indices are on the same scale (0 to 1) and directly comparable. Table 2 shows the results in more detail. For control participants both grammaticality and chunk strength performance were found to be significantly higher than chance ($t(26)=2.31$, $p=.029$, $t(26)=2.20$, $p=.037$, for grammaticality and chunk strength respectively). For TBI participants, chunk strength performance was significantly higher than chance ($t(18)=4.36$, $p<.0005$), but grammaticality performance was significantly lower compared to chance ($t(18)=-2.15$, $p=.045$), indicating that TBI patients were completely unable to utilize grammaticality appropriately as a basis for their endorsements of test items.

------------------Tables 1, 2------------------

Therefore, grammaticality and chunk strength influences on performance appear equivalent for the control participants, but for TBI patients chunk strength dominates. This was further confirmed. We ran a mixed design ANOVA, with participant status (‘TBI patient vs. control’) as a between participants factor and performance index (‘grammaticality vs. chunk strength’) as a within participants factor. There was no effect of participant status, $F(1,44)=1.27$, $p=.27$, but there was a significant effect of performance index, $F(1,44)=7.95$, $p=.007$. Crucially, there was a significant interaction between participant status and performance index, $F(1,44)=8.47$, $p=.006$. The interaction was investigated with post hoc comparisons, comparing, with paired samples t-tests, grammaticality and chunk strength performance for the control participants and TBI patients separately. For the control participants there was no difference between grammaticality and chunk strength performance: $t(26)=0.06$, $p=.95$. By contrast, for TBI patients chunk strength performance was superior to grammaticality: $t(18)=5.30$, $p<.0005$.

While the averages indicate a clear dissociation, it is possible that these results arise from a few extreme individuals. Hence, we counted the number of participants whose grammaticality performance was greater than their chunk strength performance. In the control sample, these were 12 out of 26, with 2 equalities and in the TBI group there were 2 out of 19, with 1 equality.

3. Discussion

We compared grammaticality and chunk strength influences on performance, in an AGL task, with TBI patients and matched control participants. Control participants' performance reflected equivalent influences of grammaticality and chunk strength, as typically found in AGL research (e.g., Knowlton & Squire, 1996). By contrast, TBI patients' performance reflected only knowledge of chunk strength; TBI patients appeared completely unable to utilize grammaticality to make appropriate test item selections.

Our results make sense within an interpretation of AGL using the COVIS model (Ashby et al., 1998; Zeithamova & Maddox, 2006) and support an understanding of AGL such that separate learning processes lead to knowledge of grammaticality and chunk strength (cf. Lieberman et al., 2004). According to the COVIS model, for the hypothesis-testing system to operate, an intact/developed prefrontal cortex is required (Minda et al., 2008). TBI typically results in localized and diffuse prefrontal cortex damage and it was confirmed that all TBI patients in this study had suffered contusional injury to the prefrontal cortex and exhibited problems in executive functioning. Their grammaticality performance was impaired, but their chunk strength performance was equivalent to that of matched controls.

These results help understand the nature of multiple knowledge influences in AGL. It appears that grammaticality knowledge can be developed through a hypothesis-testing system, while for chunk strength knowledge passive processing of the stimuli suffices. Such an interpretation of grammaticality would ascribe to it more 'rule-like' qualities, of the kind of rules postulated in COVIS, and unlike early suggestions of AGL, according to which learning involves a representation of the relevant finite state language (Reber, 1993; see also Pothos, 2005, 2007).

There are various qualifications to this conclusion. First, we believe that the above interpretation of grammaticality is possible only when the test stimuli carefully balance the putative influences of grammaticality and chunk strength. Without such balancing, grammaticality performance probably reflects a range of knowledge influences so that it is no longer meaningful to attach a single psychological process to grammaticality. Second, we assumed that TBI patients are just like the matched controls, but for an impaired hypothesis-testing system. It is possible that TBI patients employ compensatory strategies, which would confuse a straightforward comparison between patients and controls (cf. Smith & McDowall, 2005). Rejecting such a null hypothesis is difficult, without a greatly expanded research program. Third, we have avoided discussing whether AGL knowledge is implicit or explicit. Our results provisionally suggest that grammaticality knowledge would reflect conscious hypotheses (about the items), but chunk strength knowledge could be either implicit or explicit (cf. Dienes & Perner, 1999; Tunney & Shanks, 2003). However, this is a complicated issue beyond the scope of this research. Finally, some researchers have argued against the idea of multiple systems in learning (e.g., Nosofsky & Kruschke, 2002; Stanton & Nosofsky, 2007). Can a single computational model account for all test-item selections in an AGL experiment? Pothos and Bailey (2000) explored this issue with the generalized context model (GCM), one of the most powerful current categorization models. After fitting the GCM to AGL data, Pothos and Bailey still identified a range of independent influences from other sources of knowledge (such as grammaticality). Such a conclusion, together with relevant neuroscience data, argue against an understanding of AGL in terms of a unitary cognitive process.

Overall, we have illustrated the utility of studying TBI patients with AGL, provided the outline of a novel framework to understand grammaticality by applying the COVIS model to AGL, and identified preliminary findings for the debate on multiple learning systems in the case of AGL.

4. Experimental investigation

4.1 Participants

The TBI cohort was selected from a consecutive series of head injury cases referred to the Head Injury Clinic at Swansea University during 2007 (N=35). The patients were referred because they exhibited executive deficits during everyday activities which compromised their capacity for community independence. The control group were 31 members of the general public matched for age (in years, TBI: mean=36.10, SD=13.88; control: mean=40.9, SD=13.42), gender (TBI: male=12; control: male=15) and intelligence (TBI: mean IQ=97.41, SD=13.05, as measured by the WAIS III, Wechsler, 1998; control: mean IQ=99.30, SD=14.70, as measured using the Wechsler Test of Adult Reading which correlates highly with the WAIS III; Wechsler, 2001).

Exclusion criteria for this study comprised a pre-accident history of psychiatric and/or personality disorder; a developmental history of learning disability, based either on General Practitioner records or an estimated pre-accident IQ<70; dysphasia or any other neurological disorder that would compromise their ability to reliably complete the test; neuropsychological disability that threw doubt on capacity to agree to participate in the study. Of the original 35 patients, 19 cases met the above criteria and formed the experimental cohort.

Head injury severity was determined by the length of Post Traumatic Amnesia (PTA; in days, mean=15.74, SD=12.17) and Glasgow Coma Scores (GCS) at the time of hospital admission (mean=9.89, SD=4.54). The mean time between injury and participation in the study was 4.25 years (SD=4.44 years). TBI is associated with diffuse head trauma, predominantly affecting prefrontal and anterior temporal structures. In this cohort, all TBI participants had abnormal CT (computerized tomography) scans, indicating predominantly frontal haemorrhagic or contusional injuries: number of participants with CT scans showing predominantly a left frontal injury=7, right frontal=6, bi-lateral injury=6. During clinical interview (carried out by RLW), the TBI participants and their close relatives described problems characteristic of executive dysfunction, using the criteria of Baddeley and Della Sala, (1997). Information on executive dysfunction was also collected using a 20 item Dysexecutive Questionnaire (DEX; Wilson et al 1996). One version of the DEX is designed to be completed by the patient, another by the relative or carer who has close, preferably daily, contact with the subject. As a group, DEX-S and DEX-I ratings fell within the 75th percentile (Wilson et al., 1996), indicating major executive weaknesses in everyday life.

4. 2. Materials

Knowlton and Squire (1996) provided AGL stimuli counterbalancing grammaticality and chunk strength, but we did not employ their materials as we wanted to have more test items per subset of test stimuli. Creation of AGL stimuli (both training and test) was based on Reber and Allen's (1978) finite state language and was conducted using Bailey and Pothos' (2008) algorithm for generating AGL stimuli.

Stimuli had a length between three and seven elements, the number of training items was set to 25, and the number of test items to 40 (20 G and 20 NG; no training stimulus was repeated in test). The mean chunk strengths of G and NG items were .49 and .47 respectively. Note that in Bailey and Pothos' system chunk strength values are computed so that individual chunk strength is given as $\frac{F}{F+E}$, where F is the frequency of the chunk across all training strings, and E is the expected frequency for a chunk of that size. The chunk strength of a stimulus is the average strength of its chunks (as per Knowlton and Squire, 1994). An independent samples t-test comparing the average chunk strength between G and NG items was not significant ($t(38)=0.579$, $p=.57$). We then ordered test items in terms of their chunk strength value and called the top 20 'high chunk strength' and the bottom 20 'low chunk strength'. The average chunk strength of the low chunk strength items was .38 and of the high chunk strength items .58 ($t(38)=25.89$, $p<.0005$). Figure 1 shows the distribution of chunk strength values, and it can be seen that this is roughly bimodal both for test G and test NG items. Overall, grammaticality and chunk strength were very well-balanced.

--------------------------------Figure 1---------------------------

Stimuli were presented as letter strings (the letters used were M,S,V,X,R).

4.3 Procedure

We attempted to explain the AGL task in everyday terms, to accommodate the TBI patients, who might be alienated in a university laboratory. In the training part, participants were told to observe the stimuli they were about to see. The 25 training stimuli were then presented twice, so that no stimulus was presented twice before all stimuli had been presented at least once. Each training stimulus was shown on a computer screen for 2500ms. After training, participants were told to think of all the training items as belonging to the same category. It was explained that categories have many features in common, for example, all cars share an engine etc. Participants were informed that they were about to see some new stimuli and that some of the new stimuli were in the same category as the training ones, while others were not, and that their task was to discriminate between the two (by pressing the appropriate key). Each test stimulus was presented once, until participants made a response; no feedback was given. Once a response had been provided the next stimulus was presented straightaway.

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Tables

Table 1. Grammaticality and chunk strength performance, given as mean/ standard deviation. The performance indices for grammaticality have been computed as the proportion of G items correctly endorsed as G and the proportion of NG items correctly rejected as NG, so that chance performance is 0.50 and perfect performance is 1.00; likewise for chunk strength.

	Grammaticality	Chunk strength
Controls (N=27)	.54/ .09	.53/ .09
HT patients (N=19)	.46/ .07	.58/ .08

Table 2. Mean endorsement for the various subgroups for the test items, expressed as the proportion of items in that subgroup that have been endorsed by participants, on average (mean / standard deviation). Note that for the NG items higher endorsement implies lower grammaticality performance and, likewise, for the low chunk strength items, higher endorsement implies lower chunk strength performance.

	Control	HT
N	27	19
G, High Ch Str.	.69/ .12	.67/ .18
G, Low Ch Str.	.59/ .24	.43/ .23
NG, High Ch. Str.	.59/ .21	.67/ ./22
NG, Low Ch Str.	.53/ .19	.58/ .20

Figures and Figure captions.

Figure 1. The distribution of chunk strength values for the test G and test NG items. The bimodal character of these distributions is consistent with our intention to manipulate grammaticality and chunk strength as two categorical factors.