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Neural Responses to Structural Incongruencies in Language and Statistical Learning Point to Similar Underlying Mechanisms

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Abstract

We used event-related potentials (ERPs) to investigate the distribution of brain activity while adults performed (a) a natural language reading task and (b) a statistical learning task involving sequenced stimuli. The same positive ERP deflection, the P600 effect, typically linked to difficult or ungrammatical syntactic processing, was found for structural incongruencies in both natural language as well as statistical learning and had similar topographical distributions. These results suggest that general learning abilities related to the processing of complex, sequenced material may be implicated in language processing. We conclude that the same neural mechanisms are recruited for both syntactic processing of language stimuli and statistical learning of sequential patterns more generally.

Keywords: Event-Related Potentials; Statistical Learning; Language Processing; P600

Introduction

One of the central questions in cognitive science concerns the extent to which higher-order cognitive processes in humans are either subserved by separate, domain-specific brain mechanisms or whether the same neural substrate may support several cognitive functions in a domain-general fashion. The issue of modularity has played a particularly important role in the study of language, which has traditionally been regarded as being strongly modular (e.g., Friederici, 1995; Pinker, 1991). Given such modular characterization, the cognitive and neural machinery employed in acquiring and processing language is considered to be uniquely dedicated to language itself. Thus, on this account, little or no overlap in neural substrates would be expected between language and other higher-order cognitive processes.

Here, we explore the alternative hypothesis that the neural underpinnings of language may be part of a broader family of neural mechanisms that the brain recruits when processing sequential information in general. One such type of learning process—employed to encode complex sequential patterns and also implicated in language processing—is *implicit statistical learning*¹ (Conway &

Christiansen, 2006; Gómez & Gerken, 2000). Statistical learning involves the extraction of regularities and patterns distributed across a set of exemplars in time and/or space, typically without direct awareness of what has been learned. Though many researchers assume that statistical learning is important for language acquisition and processing (e.g., Gómez & Gerken, 2000), there is very little direct neural evidence supporting such a claim. There is some evidence from event-related potential (ERP) studies showing that structural incongruencies in non-language sequential stimuli elicit similar brain responses as those observed for syntactic violations in natural language: a positive shift in the brainwaves observed about 600 msec after the incongruency known as the P600 effect (Friederici, Steinhauer, & Pfeifer, 2002; Lelekov, Dominey, & Garcia-Larrea, 2000; Patel, Gibson, Ratner, Besson, & Holcomb, 1998). Although encouraging, the similarities are inferred across different subject populations and across different experimental paradigms. Thus, no firm conclusions can be made because there is no study that provides a direct within-subject comparison of the ERP responses to both natural language and statistical learning of sequential patterns.

In this paper, we investigate the possibility that structural incongruencies in both natural language and other sequential stimuli will elicit the same electrophysiological response profile, a P600. We provide a within-subject comparison of the neural responses to both types of violations, allowing us to directly assess the hypothesis that statistical learning of sequential information is an important cognitive mechanism underlying language processing. Such a demonstration is important for both theoretical and practical reasons. Statistical learning has become a popular method for investigating natural language acquisition and processing, especially in infant populations (e.g., Gómez & Gerken, 2000). Thus, providing direct neural evidence linking statistical learning to natural language processing is necessary for validating the statistical learning approach to language. Moreover, our study is also of theoretical importance as it addresses issues relating to the modularity of language. Before describing our ERP study, we first

¹ “Implicit learning” and “statistical learning” have traditionally been studied separately; however, we consider these two terms to

be touching on the same underlying learning mechanism, which we hereafter refer to simply as statistical learning.

briefly review recent electrophysiological evidence regarding the neural correlates of both language and statistical learning.

ERP Correlates of Language and Statistical Learning

In ERP studies of syntactic processing, the P600 response was originally observed as an increased late positivity recorded around 600 msec after the onset of a word that is syntactically anomalous (e.g., Hagoort, Brown & Groothusen, 1993; Neville, Nicol, Barss, Forster & Garrett, 1991). P600 responses were also observed at the point of disambiguation in syntactically ambiguous sentences in which participants experienced a ‘garden path’ effect (e.g., at ‘was’ in *The lawyer charged the defendant was lying*; Osterhout & Holcomb, 1992). Osterhout & Mobley (1995) found a similar P600 pattern for ungrammatical items in a study of agreement violations in natural language (e.g., *The elected officials hope/*hopes to succeed*, and *The successful woman congratulated herself/*himself*). Other violations of long-distance dependencies in natural language have also elicited P600 effects (e.g., Kaan, Harris, Gibson, & Holcomb, 2000). Across these studies, the typically observed distribution for the P600 is over central and posterior (occipital and parietal) sites.

The electrophysiological correlates of statistical learning have received much less attention. Statistical learning is primarily investigated behaviorally using some sort of variation of the artificial grammar learning (AGL) paradigm (Reber, 1967), in which a finite-state “grammar” is used to generate sequences conforming to arbitrary underlying rules of correct formation. After relatively short exposure to a subset of sequences generated by an artificial grammar, subjects are able to discriminate between correct and incorrect sequences with a reasonable degree of accuracy, although they are typically unaware of the constraints that govern the sequences. This paradigm has been used to investigate both implicit learning (e.g., Reber, 1967) and language acquisition (e.g., Gomez & Gerken, 2000).

It is possible that the neural processes recruited during artificial grammar learning of sequential stimuli may be at least partly coextensive with neural processes implicated in natural language (see also Hoen & Dominey, 2000). If this hypothesis holds, it should be possible to find similar neural signatures to violations in AGL sequences and natural language sequences alike. Indeed, Friederici et al. (2002) found natural language-like ERP responses from participants who had learned an artificial language. One of these responses, a P600, was also observed for incongruent musical chord sequences by Patel et al. (1998), who detected no statistically significant differences between the P600 for syntactic and musical structural incongruities.

These studies suggest that the P600 may reflect the operation of a general neural mechanism that handles sequential patterns, whether linguistic or not. Therefore, we set out to assess ERP responses in adult subjects on two separate tasks, one involving statistical learning and the

other involving the processing of English sentences. We hypothesized that overlapping, at least partially but perhaps entirely, neural processes subserve both statistical learning and natural language processing, and thus anticipated obtaining a similar brain response, the P600, to structural incongruities in both tasks.

Method

Participants

Eighteen students (17 right-handed; 5 male) from Cornell University participated in one session and were paid for their participation. Data from an additional 4 participants were excluded because more than 25% of experimental trials were contaminated due to an excessive number of eye blinks/movements ($n=3$) or poor data quality ($n=1$). The age of the remaining participants ranged between 18 and 22 years ($M = 19.8$). All were native speakers of English.

Stimulus Materials

Statistical learning (SL) task A miniature grammar (see Figure 1.a)—a slightly simplified version of that used by Friederici et al. (2002)—was used to produce a set of “sentences” consisting of the form subject-verb-object (with object being optional). The grammar specifies four types of word categories, each with a particular number of tokens that can comprise it: Noun (N_1, N_2, N_3), Verb (V_1, V_2, V_3), Adjective (A_1, A_2), and Determiner, the latter containing two subcategories of articles with different distributional properties (d, D). These categories are indicated in Figure 1.a as N, V, A, d, and D, respectively. The grammar produces sentences composed of nonword tokens, randomly assigned to the categories for each subject from a set of 10 unique tokens: *jux, dupp, hep, meep, nib, tam, sig, lum, cav, and biff*. Each sentence describes a visual scene (i.e., a referent world) consisting of graphical symbols arranged in specific ways. For example, each Noun nonword token had a corresponding shape referent; likewise, each Verb nonword token also had a corresponding referent (circle, octagon, square). The Determiner and Adjective tokens did not have their own symbols but instead affected the color of the Noun referents. That is, a Noun preceded by *d* meant that the Noun referent would be black; a Noun preceded by *D* A_1 denoted a green Noun referent while *D* A_2 resulted in a red Noun referent. Note the distributional restriction that *d* never occurs with an Adjective whereas *D* is always followed by one.

Sixty sentences from the grammar were used for the Learning Phase. The nonword form of the sentences consisted of written nonword strings (e.g., *nib cav jux*). Each nonword string produced from the grammar described a visual scene consisting of the Noun and Verb referents described above. Verb referents always occurred in the center of the screen. Noun referents appeared either inside the Verb referent (for subject Nouns) or outside of the Verb referent, to the upper right (for object Nouns). An example of a visual scene is shown in Figure 1.b.

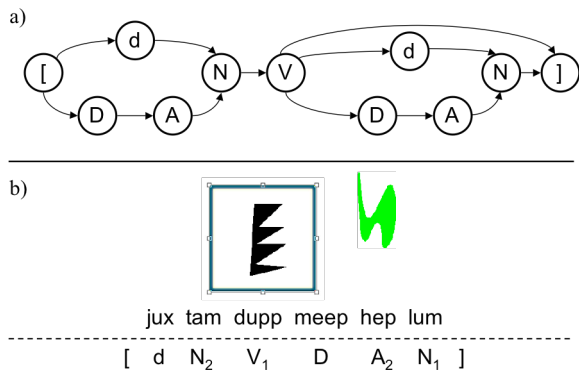


Figure 1: a) The artificial grammar used to generate the adjacent dependency language. The nodes denote word categories and the arrows indicate valid transitions from the beginning node (I) to the end node (J). b) An example sentence with its associated visual scene (the sequence of word categories below the dashed line is for illustrative purposes only and was not shown to the participants).

An additional 30 grammatical sentences were used for the Test Phase. Thirty ungrammatical sentences were additionally used for the Test Phase. To derive violations for the ungrammatical sentences, tokens of one word category in a grammatical sentence were replaced with tokens from a different word category.

Natural language (NL) task Two lists, List1 and List2, containing counter-balanced sentence materials were used for the natural language task, adapted from Osterhout and Mobley (1995). Each list consisted of 60 English sentences, 30 being grammatical and 30 having a violation in terms of subject-verb number agreement (e.g., *Most cats likes to play outside*). One additional list of 60 sentences was used as filler materials, also adapted from Osterhout and Mobley (1995). The filler list had 30 grammatical sentences and 30 sentences that had one of two types of violation: antecedent-reflexive number (e.g., *The Olympic swimmer trained themselves for the swim meet*) or gender (e.g., *The kind uncle enjoyed herself at Christmas*) agreement.

Procedure

Participants were tested individually, sitting in front of a computer monitor. The participant's left and right thumbs were each positioned over the left and right buttons of a button box. All subjects participated in the SL task first and the NL task second.

Statistical learning task Participants were instructed that their job was to learn an artificial "language" consisting of new words that they would not have seen before and which described different arrangements of visual shapes appearing on the computer screen. The SL task consisted of two phases, a Learning Phase and a Test Phase, with the Learning Phase itself consisting of four sub-phases.

In the first Learning sub-phase, participants were shown a Noun or a Verb, one at a time, with the nonword token displayed at the bottom of the screen and its corresponding visual referent displayed in the middle of the screen. Participants could observe the scene for as long as they

liked and when they were ready, they pressed a key to continue. All three Verbs but only the three Nouns preceded by d were included (i.e., only the black Noun referents). The 6 words were presented in random order, 4 times each for a total of 24 trials.

In the second Learning sub-phase, the procedure was identical to the first sub-phase but now the other six Noun variations were included, those preceded by D A₁ or D A₂ (i.e., the red and green Noun referents). The 9 Nouns and 3 Verbs were presented in random order, two times each, for a total of 24 trials.

In the third Learning sub-phase, full sentences were presented to participants, with the nonword tokens presented below the corresponding visual scene. The 60 Learning sentences described above were used for this sub-phase, each presented in random order, 3 times each.

In the fourth and final Learning sub-phase, participants were again exposed to the same 60 Learning sentences but this time the visual referent scene appeared on its own, prior to displaying the corresponding nonword tokens. First, a visual scene was shown for 4 sec, and then after a 300 msec pause, the nonword sentences that described the scene were displayed, one word at a time (duration: 350 msec; ISI: 300 msec). The 60 Learning sentences/scenes were presented in random order.

In the Test Phase, participants were told that they would be presented with new scenes and sentences from the artificial language. Half of the sentences would describe the scenes according to the same rules of the language as before, whereas the other half of the sentences would contain an error with respect to the rules of the language. The participant's task was to decide which sentences followed the rules correctly and which did not by pressing a button on the response pad. The visual referent scenes were presented first, none of which contained grammatical violations, followed by the nonword sentences (with timing identical to Learning sub-phase 4). After the final word of the sentence was presented, a 1400 msec pause occurred, followed by a test prompt asking for the participant's response. The 60 Test sentences/scenes were presented in random order, one time each.

Natural language task Participants were instructed that they would be presented with English sentences appearing on the screen, one word at a time. Their task was to decide whether each sentence was acceptable or not (by pressing the left or right button), with an unacceptable sentence being one having any type of anomaly and would not be said by a fluent English speaker. Before each sentence, a fixation cross was presented for 500 msec in the center of the screen, and then each word of the sentence was presented one at a time for 350 msec, with 300 msec occurring between each word (thus words were presented with a similar duration and ISI as in the SL task). After the final word of the sentence was presented, a 1400 msec pause occurred followed by a test prompt asking the subject to make a button response regarding the sentence's acceptability. Participants received

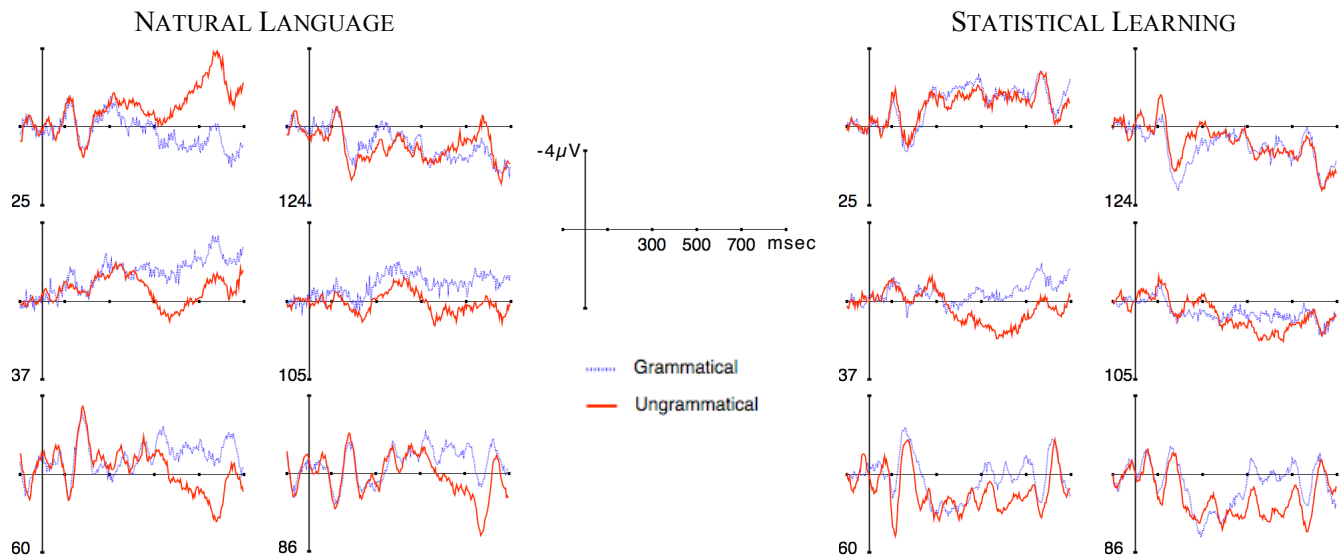


Figure 2: Grand average ERPs elicited for target words for grammatical (dashed) and ungrammatical (solid) continuations in the natural language (left) and statistical learning (right) tasks. The vertical lines mark the onset of the target word. Six electrodes are shown, representative of the left-anterior (25), right-anterior (124), left-central (37), right-central (105), left-posterior (60), and right-posterior (86) regions. Negative voltage is plotted up.

a total of 120 sentences, 60 from List1 or List2 and 60 from the Filler list.

EEG Recording and Analyses

The EEG was recorded from 128 scalp sites using the EGI Geodesic Sensor Net (Tucker, 1993) during the Test Phase of the SL task and throughout the NL task. All electrode impedances were kept below 50 k Ω . Recordings were made with a 0.1 to 100-Hz bandpass filter and digitized at 250 Hz. The continuous EEG was segmented into epochs in the interval -100 msec to +900 msec with respect to the onset of the target word that created the structural incongruity.

Participants were visually shown a display of the real-time EEG and observed the effects of blinking, jaw clenching, and eye movements, and were given specific instructions to avoid or limit such behaviors throughout the experiment. Trials with eye-movement artifacts or more than 10 bad channels were excluded from the average. A channel was considered bad if it reached 200 μ V or changed more than 100 μ V between samples. This resulted in less than 11% of trials being excluded, evenly distributed across conditions. ERPs were baseline-corrected with respect to the 100-msec pre-stimulus interval and referenced to an average reference. Separate ERPs were computed for each subject, each condition, and each electrode.

Following Barber and Carreiras (2005), six regions of interest were defined, each containing the means of 11 electrodes: left anterior (13, 20, 21, 25, 28, 29, 30, 34, 35, 36, and 40), left central (31, 32, 37, 38, 41, 42, 43, 46, 47, 48, and 50), left posterior (51, 52, 53, 54, 58, 59, 60, 61, 66, 67, and 72), right anterior (4, 111, 112, 113, 116, 117, 118, 119, 122, 123, and 124), right central (81, 88, 94, 99, 102, 103, 104, 105, 106, 109, and 110), and right posterior (77, 78, 79, 80, 85, 86, 87, 92, 93, 97, and 98).

We performed analyses on the mean voltage within the same three latency windows as in Barber and Carreiras (2005): 300-450, 500-700, and 700-900 msec. Separate repeated-measures ANOVAs were performed for each latency window, with grammaticality (grammatical and ungrammatical), electrode region (anterior, central, and posterior), and hemisphere (left and right) as factors. Geisser-Greenhouse corrections for non-sphericity of variance were applied when appropriate. Because the description of the results focuses on the effect of the experimental manipulations, effects related to region or hemisphere are only reported when they interact with grammaticality. Results from the omnibus ANOVA are reported first followed by planned comparisons.

Results

Grammaticality Judgments

Of the test items in the SL task, participants classified 93.9% correctly. In the NL task, 92.9% of the target noun/verb-agreement items were correctly classified. Both levels of classification were significantly better than chance (p 's < .0001) and not different from one another (p > .5).

Event-Related Potentials

Figure 2 shows the grand average ERP waveforms for grammatical and ungrammatical trials across six representative electrodes (Barber and Carreiras, 2005) for the NL (left) and SL (right) tasks. Visual inspection of the ERPs indicates the presence of a left-anterior negativity (LAN) in the NL task, but not in the SL task, and a late positivity (P600) at central and posterior sites in both tasks, with a stronger effect in the left-hemisphere and across

posterior regions. These observations were confirmed by the statistical analyses reported below.

300-450 msec latency window For the NL data there was a two-way interaction between grammaticality and hemisphere ($F(1,17) = 4.71, p < .05$). An effect of grammaticality was only found for the left-anterior region, where ungrammatical items were significantly more negative ($F(1,17) = 9.52, p < .007$), suggesting a LAN. No significant main effects or interactions related to grammaticality were found for the SL data.

500-700 msec latency window There was an overall effect of grammaticality ($F(1,17) = 15.96, p < .001$) and a significant interaction between grammaticality and region in the NL data ($F(2,34) = 8.88, p < .002, \epsilon = .77$). This interaction arose due to the differential effect of grammaticality across the anterior and central regions ($F(1,17) = 17.55, p < .001$). Whereas the negative deflection elicited by the ungrammatical items continued across the left-anterior region ($F(1,17) = 5.49, p < .04$), a positive wave was observed for both posterior regions (left: $F(1,17) = 15.23, p < .001$; right: $F(1,17) = 9.40, p < .007$) and marginally significant for the left-central region ($F(1,17) = 3.16, p = .093$), indicative of a P600 effect.

For the SL data, there was an overall effect of grammaticality ($F(1,17) = 13.94, p < .002$). A positive deflection was observed across the left- and right posterior regions ($F(1,17) = 5.74, p < .03$; $F(1,17) = 4.53, p < .05$) and marginally significant for the left-central region ($F(1,17) = 4.32, p = .053$) suggesting a P600 effect similar to the one elicited by natural language.

700-900 msec latency window A grammaticality \times region \times hemisphere interaction was found ($F(2,34) = 3.65, p < .04, \epsilon = .98$) for the NL data, along with a grammaticality \times region interaction ($F(2,34) = 12.66, p < .001, \epsilon = .72$) and an overall effect of grammaticality ($F(1,17) = 9.46, p < .007$). Both interactions were driven by the differential effects of grammaticality on the ERPs in the anterior and central regions ($F(1,17) = 21.25, p < .0001$), combined with a hemisphere modulation in the three-way interaction ($F(1,17) = 4.81, p < .05$). The negative deflection for ungrammatical items continued in the left-anterior region ($F(1,17) = 13.93, p < .002$), as did the positive wave across left- and right-posterior regions ($F(1,17) = 11.70, p < .003$; $F(1,17) = 11.38, p < .004$), and which now also emerged over the right-central region ($F(1,17) = 5.69, p < .03$).

A marginal overall effect of grammaticality was found for the SL data ($F(1,17) = 3.88, p = .065$). In this time window the positive-going deflection had all but disappeared except for a marginal effect across the left-central region ($F(1,17) = 4.23, p = .055$).

Comparison of Language and Statistical Learning

To more closely compare the ERP responses to structural incongruencies in language and statistical learning, we computed ungrammatical-grammatical difference waves for each electrode site. Figure 3 shows the resulting waveforms

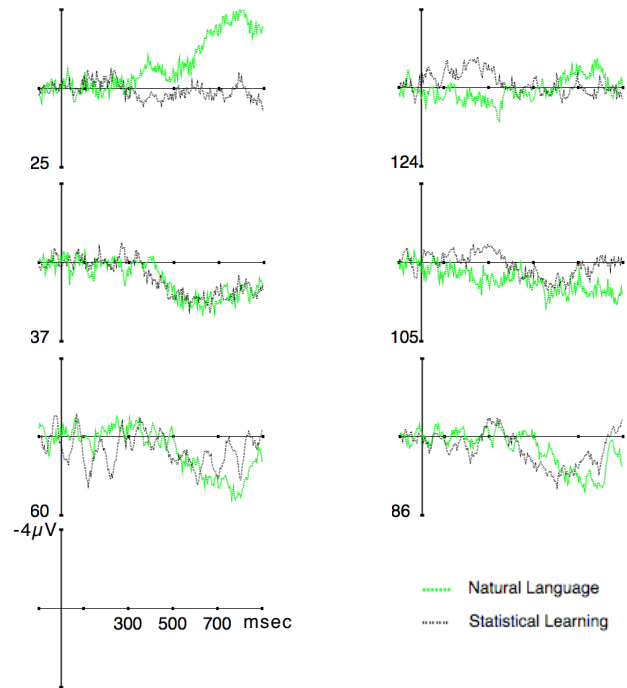


Figure 3: Difference waves (ungrammatical minus grammatical) for the language (light-colored) and statistical learning (dark-colored) tasks.

for our six representative electrodes. NL and SL difference waves were compared in the latency range of the P600: we conducted a repeated-measures analysis between 500 and 700 msec with task as the main factor.

There was no main effect of task ($F(1,17) = .03, p = .87$), nor any significant interactions with region ($F(2,34) = 1.47, p = .246, \epsilon = .71$) or hemisphere ($F(1,17) = .45, p = .511$). However, there was a marginal three-way interaction ($F(2,34) = 2.77, p = .077$) but this was due to the differential modulation of the task and hemisphere factors in the anterior and central regions ($F(1,17) = 4.29, p = .054$). Indeed, planned comparisons indicated that only in the left-anterior region was there a significant effect of task due to the LAN-associated negative-going difference wave for the language condition ($F(1,17) = 4.95, p < .04$). No other effects of task were found (F 's $< .6$).

Because LAN has been hypothesized to arise from different neural processes than the P600 (e.g., Friederici, 1995), our data suggest that the P600 effects we observed in both tasks are likely to be produced by the same neural generators. This suggestion is further supported by a regression analysis in which we used the difference between ungrammatical and grammatical responses averaged across the posterior region for the SL task to predict the mean difference elicited by the NL task in the same region. The analysis revealed a significant correlation between P600 effects across tasks ($R = .50, F(1,16) = 5.34, p < .04$): the stronger a participant's P600 effect was in the SL task, the more pronounced was the corresponding NL P600 in the NL task. The close match between the NL and SL P600 effects is particularly striking given the difference in violations across the two tasks (NL: agreement; SL: word category).

Discussion

This study provided the first direct comparison of electrophysiological brain signatures of statistical learning and language processing using a within-subject design. The advantage of such a design is that inter-individual variance is held constant, unlike previous studies that compared neural responses between different individuals participating in different experiments. Following a brief exposure to structured sequences in an SL task incorporating visual stimuli, our participants showed evidence of having implicitly learned the constraints governing the sequences of stimuli. Crucially, sequences that contained structural incongruencies elicited a P600 signature that was statistically indistinguishable from the P600 elicited by syntactic violations in the NL task.

One difference between the ERP data from the two tasks was that we observed a LAN for the NL task but not for the SL task. The LAN is sometimes observed following syntactic violations and is thought to reflect a relatively automatic parsing process (Friederici et al., 2002). However, as in our study, the LAN was absent following both musical sequential incongruencies (Patel et al., 1998) and violations of a miniature version of Japanese (Mueller, Hahne, Fujii & Friederici, 2005). One possible explanation is that the LAN reflects a truly language-specific neural process; yet, it is perhaps more likely that the LAN denotes a response to incongruencies in overly-learned patterns, such as language. Indeed, the results from the Friederici et al. (2002) artificial grammar learning study suggest that with extensive training a LAN effect can be obtained. Thus, we suggest that the lack of a LAN-type effect in our SL task might signal differences in the two tasks relating to the vastly different amount of experience that our participants had with the English language versus the patterned stimuli of the SL task.

What is much more certain given our results is that the P600 does not appear to be language-specific. That both tasks elicited the same P600-type signature suggests that the same overlapping neural mechanisms are involved in both language processing and statistical learning. This validates the application of SL paradigms toward the study of language acquisition and processing, and suggests that the SL approach will be a fruitful way of studying language. Finally, our study has important theoretical implications regarding the nature of the neural mechanisms recruited during language learning and processing. The results suggest that brain areas responsible for processing words in sequences are at least partly coextensive with brain areas responsible for processing other types of complex sequential information such as sequences of sounds, visual objects, or events in general. Thus, we conclude that the neural processes recruited for human abilities involving the encoding, organization, and production of temporally unfolding events are likely to be shared by processes typically attributed to language.

Acknowledgments

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