

Visual linguistic statistical learning is traceable through neural entrainment

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Abstract

The human brain can detect statistical regularities in the environment across a wide variety of contexts. The importance of this process is well-established not just in language acquisition but across different modalities; in addition, several neural correlates of statistical learning have been identified. A current technique for tracking the emergence of regularity learning and localizing its neural background is frequency tagging (FT). FT can detect neural entrainment not only to the frequency of stimulus presentation but also to that of a hidden structure. Auditory learning paradigms with linguistic and nonlinguistic stimuli, along with a visual paradigm using nonlinguistic stimuli, have already been tested with FT. To complete the picture, we conducted an FT experiment using written syllables as stimuli and a hidden triplet structure. Both behavioral and neural entrainment data showed evidence of structure learning. In addition, we localized two electrode clusters related to the process, which spread across the frontal and parieto-occipital areas, similar to previous findings. Accordingly, we conclude that fast-paced visual linguistic regularities can be acquired and are traceable through neural entrainment. In comparison with the literature, our findings support the view that statistical learning involves a domain-general network.

KEYWORDS

artificial grammar learning, EEG, frequency tagging, reading, statistical learning

1 | INTRODUCTION

Our ever-changing environment feeds us a continuous stream of information. Statistical learning (SL) allows us to acquire the transitional probabilities (TP) between stimuli, which helps us segment the stream into sensible information chunks (Schapiro & Turk-Browne, 2015). Additionally, stimuli can become predictable based on TPs that can facilitate sensory processing, aiding our perception (Rao & Ballard, 1999). In this study, we tested whether

we could observe SL using written syllables as stimuli, and if so, whether it can be traced with EEG techniques.

SL has been observed across multiple modalities (Kaposvári et al., 2018; Lammertink et al., 2019) and age groups (Nemeth et al., 2013; Zwart et al., 2019), even in some nonhuman species (Santolin & Saffran, 2018) and it is considered to be a general ability in sensory stimulus processing, which can be achieved with unattended stimuli as well (Batterink & Paller, 2019; Musz et al., 2015). It was first described in an artificial language paradigm in 8-month-old

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infants (Saffran et al., 1996) and since then, its effects have been found in visual (Fiser & Aslin, 2002), tactile (Conway & Christiansen, 2005) and multimodal paradigms (Seitz et al., 2007), both in children (Bertels et al., 2015) and adults (Sáringner et al., 2022). A particularly popular topic in the context of SL is its role in linguistics and language acquisition. SL might be a key component in language acquisition for infants, as the speech they hear is a continuous auditory stream (Romberg & Saffran, 2010). Contrary to intuitive belief, there are no clear pauses between spoken words during natural speech that would be similar to spaces between written words, rendering the segmentation of continuous speech into separate words a difficult task. Although a conscious effort to speak clearly can highlight word boundaries with specific cues (Cutler & Butterfield, 1991), these are not present in everyday communication. Segmentation, however, can be more clearly performed based on the TPs between syllables: syllables within a word have higher TPs due to their frequent co-occurrence than TPs between syllables spanning across two words. Based on this phenomenon, a frequently used paradigm in SL studies is artificial grammar learning (AGL), during which participants are exposed to a computer-generated language stream where words can be discovered based on syllable TPs (Batterink et al., 2015).

SL shows a great variance across participants, which suggests that every person has a different level of affinity toward environmental statistical information (Bogaerts et al., 2022). It is debated whether this affinity is modality-specific, meaning every modality-sensitive cortical area has their own network for the processing of statistical information or there is a general SL ability with a center that computes the statistical aspects of interstimulus relationships regardless of the modality. Some evidence suggests that SL ability is domain-general because participants show similar behavioral results (i.e., reaction time change) in paradigms using different modalities (Conway & Pisoni, 2008). This debate also raises a question about the neural background of SL. A general SL affinity regardless of stimulus modality suggests that SL has one center that modulates modality-specific cortical areas. Imaging studies have proposed several potential SL centers. Plausible candidates could be the hippocampus and the medial temporal lobe, due to their role in memory processes. Studies have shown hippocampal activity changes during the acquisition of statistical information, both in auditory and visual paradigms (Covington et al., 2018; Turk-Browne et al., 2010), but the need for the hippocampus is not well established (Covington et al., 2018; Schapiro et al., 2014). The basal ganglia, particularly the striatum, has been involved in parallel with the medial temporal lobe in implicit learning and SL paradigms (Karuza et al., 2013). Memory processes in these regions can have a key role in storing TPs and adjacent stimuli (Turk-Browne et al., 2009). Apart from the already mentioned regions, an activity change in the

inferior frontal gyrus (IFG) has been observed in an AGL paradigm. The role of the IFG was assumed to be the segmentation of stimulus streams based on the evaluation of TPs (Fedorenko et al., 2012; Karuza et al., 2013; McNealy et al., 2006). Notably, these findings are not contradictory since the term SL involves several cognitive processes from basic perception and information storage to recollection and implicit use of learned patterns; thus, it is reasonable to assume that a widely spread network is active in the background (Sherman et al., 2020).

This point of view suggests domain-generality based on the involvement of domain-general cognitive processes discussed above however, another possibility is that every modality-specific cortical area is sensitive to statistical information on its own; behavioral results can support this theory as well (Siegelman & Frost, 2015). Neural evidence upholds the theory that SL essentially occurs within modality-specific cortical areas. Cortical function modulation has been observed in SL paradigms, where certain modalities activated associated domain-specific areas (Frost et al., 2015).

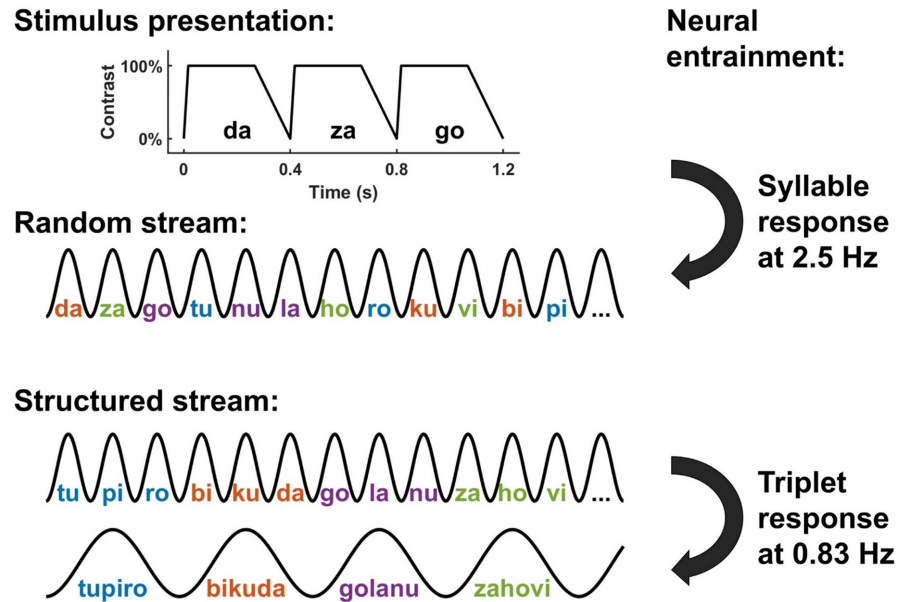
A powerful tool to trace natural correlates of SL is frequency tagging (FT). In FT paradigms, stimuli are presented at a given frequency and the corresponding neural activity would be entrained to this frequency. The detection is allowed by high temporal resolution neural data, essentially from EEG, MEG, or ECoG. If a certain regularity is hidden in the stimulus sequence (for example, triplets of syllables always forming the same artificial words), the cortical areas involved in SL should show enhanced activity at the same frequency as the regularity (in the current example, this would be at one-third of the syllable frequency). With this technique, SL emergence can be demonstrated, and SL-performing cortical areas identified. FT has been successfully implemented in auditory linguistic (Batterink & Paller, 2017; Henin et al., 2021; Pinto et al., 2022), auditory nonlinguistic (Moser et al., 2021), and visual nonlinguistic learning paradigms (Henin et al., 2021), wherein the central electrodes showed neural entrainment to the structure.

The role of SL in reading is well established; literate people are sensitive to letter and word TPs, the co-occurrence of lexical units, and the predictability of words in sentences that facilitate the reading process (Sawi & Rueckl, 2019). To our knowledge, FT has not been used in a visual linguistic SL paradigm, and the identification of cortical areas linked to such processes is long needed. Moreover, a comparison of the neural correlates of visual linguistic SL with auditory linguistic and visual nonlinguistic paradigms could help clarify the domain-general vs. modality-specific SL question.

Although FT is increasingly applied to reading research, it is usually implemented in oddball paradigms

FIGURE 1 Paradigm design.

Written syllable stimuli are presented every 400 ms, resulting in a 2.5 Hz neural response. When the stimuli are structured in triplets, a lower frequency response entrained to the regularity is expected.



(fast periodic visual stimulation), testing the differential representation of an oddball stimulus compared to a stream of background stimuli (e.g. Lochy et al., 2016; Pescuma et al., 2022). Such paradigms test how the already formed networks function when processing different stimuli and are not based on novel relationships between stimuli. De Rosa et al. (2022) designed a study in which their oddballs only differed from the background stimuli in their relative occurrence rate (oddballs were less frequent), which already hints at its potential role in SL research.

In the current study, we conducted a visual linguistic¹ FT experiment using a classic AGL paradigm. Our hypothesis was that a visual syllable stream with hidden regularities could elicit activity differences at regularity-specific frequencies, traceable across the scalp. We expected that if detectable, the scalp distribution of such entrainment would be similar to what has previously been observed in FT methods, regardless of modality. To test this, written syllables were presented in two sequences, one random and then one structured; in the latter, triplets of syllables formed artificial words. In both sequences, the syllable frequency emerged very similarly whereas the triplet frequency showed the superiority of the structured sequence. We traced the triplet-related activity on the scalp and found a great frontal electrode cluster in the midline along with a parieto-occipital cluster.

¹The claimed linguistic nature of our paradigm is based on the phenomenon that orthographic stimuli of a writing system well-known to the observer are automatically processed as linguistic units. The automatic orthographic processing makes sensible information chunks very salient and hard to ignore as exemplified by the famous Stroop color test. We thus argue that our design is not purely visual.

2 | METHODS

2.1 | Design

In our experiment, two sequences of 900 syllables, first a random and then a structured one, were displayed on a screen (Figure 1). The syllables followed each other at a frequency of 2.5 Hz (every 400 ms), so each sequence was 6 min long. In the structured stream, groups of three syllables would always appear in the same order, forming artificial words at a frequency of 0.83 Hz (every 1200 ms). During stimulation, attention was maintained with a simple 1-back detection task on 45 repeated syllables scattered throughout each sequence. A 64-channel EEG was used to identify the neural correlates of SL during stimulation. After the second sequence, the learning of the sequence structure was behaviorally tested in an explicit two-alternative forced choice (2AFC) task.

2.2 | Stimuli

We chose 12 syllables inspired by the artificial words of (Saffran et al., 1996) that had been utilized in several AGL paradigms (Misyak & Christiansen, 2012; Pavlidou & Bogaerts, 2019; Reber, 1967). These syllables were then used to generate random and structured sequences. To balance the occurrence of syllables, all 12 syllables would appear in blocks of 12 trials. This means every syllable must be presented before a syllable can reappear; thus, the exposure and familiarity of the different syllables are controlled. In the random sequence, the TP between all syllables was equal (~1/11) whereas the syllables constituted triplets in the structured sequence. The only limitation in the pseudorandom

sequence of the random stream was that a syllable can only reappear if at least 3 different syllables have been shown to reduce repetition suppression effect. This, of course, could only happen at the junction of the 12-trial blocks.

In the structured stream individual triplets always had the same syllables in their first, second, and third positions, resulting in four different artificial words. The structured sequence was also designed in a way that all 12 syllables, and thus all four triplets, would appear in a block of 12 trials. The sequences were 900 items in length, so each syllable appeared 75 times; in the structured stream, each triplet appeared 75 times.

Forty-five repetitions were introduced into each sequence for the 1-back detection task. To avoid shifting the triplet phases, these repeated syllables overwrote the original ones in the sequence in any of the three positions. Although this occasionally breaks the structure rule, it does not tilt the position of triplets in the sequence, which could interfere in FT. The repetitions were placed in a pseudorandom manner, appearing once randomly in every 20-trial block.

Each item for the familiarization 2AFC task was created by appending three syllables. Four words were created from the triplet syllables (*tupiro*, *bikuda*, *golanu*, *zahovi*), and four foil nonwords were created from syllables that did not appear together in any triplet (*tulavi*, *bihonu*, *gopida*, *zakuro*). The syllables of nonwords were position-matched, i.e., the first syllable is borrowed from the first position of a triplet, the second syllable is from the second position of a different triplet and the third syllable is also from the third position. Thus, in the structured block, the syllables would always follow one another in the same order as observed in words but never as in nonwords.

2.3 | Participants

Twenty-nine university students (mean age 21.9 years old, 20 females, 9 males) participated in the experiment for course credits. Participants were required to have normal or corrected-to-normal vision and no reading difficulties; all were native Hungarians. All procedures were conducted with the approval of the Ethics Committee of the University of Szeged and in line with the Declaration of Helsinki (170/2022_SZTE RKEB).

2.4 | Procedure

The experiment was conducted in a quiet room with dimmed light. After providing informed consent, participants were seated approx. 57 cm from the computer screen. For EEG data acquisition, a Biosemi system was used; 64 scalp electrodes were placed using head-size-matching caps

and four EOG electrodes were placed around the eyes: one above and another under the left eye, and two on the outer canthi of both eyes. Before starting the experiment, baseline activity was measured for 90s using an empty gray display.

The stimulation was carried out with Psychtoolbox 3 (Brainard, 1997; Kleiner et al., 2007) in Matlab running under Microsoft Windows. The syllable stimuli were printed in the middle of the screen in black lowercase letters on a gray background. On presentation, each stimulus lasted for 400 ms, with a sharp appearance and a 133 ms linear fade-out.

Participants were asked to attend to the stimuli and press the space key when they detected the repetition of a syllable (appearing twice in succession). The detection time window was set to 1 s from the repeated stimulus onset; a keypress outside this period was coded as a false alarm. Participants were instructed to be as quick and accurate as possible. The sequences started after a short practice session of the detection task.

After completing a random and a structured sequence (~6 min each), the participants were informed about the triplet structure and asked to identify the artificial words in a 2AFC task. A word and a nonword were presented side-by-side; participants had to choose which was more familiar by pressing the 'x' or 'm' keys. Each word-nonword pairing was tested twice (the artificial word appearing once on the left and once on the right side), to a total of 32 trials in pseudorandom order.

2.5 | EEG data processing

EEG processing and the following analyses were performed in Matlab using the FieldTrip toolbox (Oostenveld et al., 2010) and custom-written scripts. Raw EEG data were downsampled to 128 Hz and bandpass filtered between 0.1–20 Hz. To remove blink artifacts, we used a denoising source separation algorithm (Särelä et al., 2005), trained on blink events identified by vertical EOG peaks. The identified blink components were subtracted from the EEG data. Noisy channels were interpolated. The data were subsequently epoched to 4.8 s pseudotrials, spanning 12 syllable presentations (four triplet presentations).² Frequency decomposition was performed by fast-Fourier transformation in the 0.5–3 Hz frequency range using sliding window and Hanning taper method (Benjamin et al., 2021; Kamphuisen et al., 2008; Moser et al., 2021) implemented in Fieldtrip. For the frequency analysis,

²Thanks to the balanced sequence design, all 12 syllables are different and are seen only once in a pseudotrial. Also, the length of a pseudotrial is an integer multiple of the presentation time of triplets, thus triplet phase is synced across pseudotrials.

10.1 s pads (data from neighboring segments of the recording) were applied to each pseudotrial to enhance spectral resolution (0.04 Hz) and avoid signal loss at the lowest frequencies (Batterink & Paller, 2017, 2019; Benjamin et al., 2021). Sliding windows of 5 s (length of the pseudotrial) were applied to the epoch in steps of 7.8 ms (1/sampling rate).

To trace neural entrainment, the intertrial phase coherence (ITPC) was calculated according to Kabdebon et al. (2015). For further analysis, the phase of the frequency representations was retrieved for all pseudotrials.

2.6 | Statistical analysis

2.6.1 | Behavioral measures

The data from the detection task were tested for differences in reaction time (RT) and detection sensitivity. Responses within a 1 s window from a repetition were coded as correct, all other responses were considered false alarms. Correct RTs were averaged by sequence condition for all participants; similarly, d' values were calculated for each subject by sequence. RT and d' data were tested by paired Student's t -tests. In the familiarity test, the mean correct response rates for all participants were compared to chance level (0.5) by a one-sample t -test.

2.6.2 | Neural entrainment

ITPC was calculated for all channels across all pseudotrials of both sequences between 0.5 and 3 Hz. To assess neural entrainment to the triplet structure, the coherence values were averaged along the channel dimension (Pinto et al., 2022). A paired t -test with Bonferroni correction (Lewis et al., 2018) was used to test the effect at the triplet (0.83 Hz) and syllable frequencies (2.5 Hz). Additionally, the first harmonic of the triplet frequency (1.67 Hz) was also evaluated based on positive results in the literature (Batterink & Paller, 2017; also, effects at the harmonics are routinely summed in oddball paradigms e.g. De Rosa et al., 2022). Subsequently, to observe the scalp distribution of the coherence and identify triplet-sensitive channels, permutation-based statistics with cluster-based correction were used with 1000 Monte Carlo iterations implemented in Fieldtrip. After permutation, only clusters with a summed t -value >95% of the simulated population were accepted.

To evaluate phase relationships between two ITPC clusters, we used inter-site phase clustering (ISPC, Billeke et al., 2014). To reduce the skewing effect of neighboring channels, the scalp current density was calculated using

the surface Laplacian of the EEG data. To calculate the ISPC, the phase angles (from the frequency decomposition) were averaged along the channels within a cluster. ISPC was derived from the ITPC of the phase difference between two clusters. In case of connectivity, the phase angle differences should be more constant; thus, the ITPC of the phase angle differences should be higher in the structured sequence compared to the random one. Significance in ISPC was tested using a paired t -test.

In a second round of ISPC analysis, we tested whether the ISPC values are greater for the predefined clusters compared to a randomly permuted distribution, using z statistics. The distribution was drawn from 10,000 iterations, where in each round, the channels with significant ITPC were randomly assigned into two clusters. First, we tested whether our cluster definition has higher (above the 95th percentile of the sample) ISPC than randomly defined clusters in case of the random and structured trials, respectively. Subsequently, we also calculated the ISPC difference between the random and structured conditions, and tested if this is greater for the predefined cluster than the randomly permuted population (above 97.5th percentile).

3 | RESULTS

3.1 | Behavioral results

The behavioral data of one participant were accidentally lost during acquisition, so the analyses utilized data only from the remaining 28 participants. In the detection task, RT between the random (501 ms) and structured sequences (514 ms) did not differ significantly ($t(27) = 1.180$, $p = .248$). However, the detection sensitivity was higher during the structured sequence (Figure 2; $t(27) = 3.856$, $p < .001$).

The familiarity test indicated chance performance ($p_{\text{correct}} = .48$, $t(27) = -0.814$, $p = .423$). The heatmap in Figure 3 shows the mean accuracies of all word-nonword pairings and could indicate bias toward certain syllable triplets.

3.2 | Neural entrainment

First, the ITPC values averaged across all channels were tested at the triplet (0.83 Hz), first harmonic of triplet (1.67 Hz), and syllable frequencies (2.5 Hz; Table 1). Due to the Bonferroni correction, p values are multiplied by three. At 0.83 Hz, the difference between the random and structured sequences (Figure 4) was significant ($t(28) = 4.502$, $p_{\text{raw}} < .001$, $p_{\text{corrected}} < .001$). At the

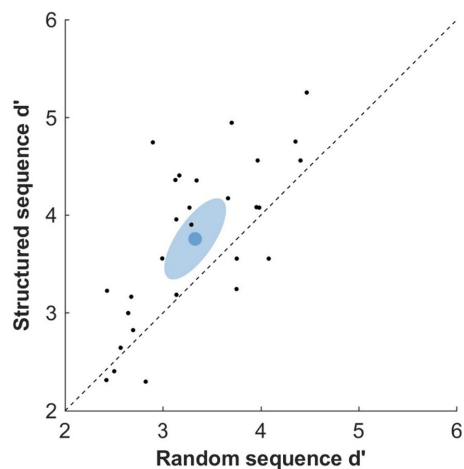


FIGURE 2 Detection task d' s from the two sequences. Each dot represents a participant and the colored marker and shaded area indicate the mean and the 95% confidence ellipse of the mean.

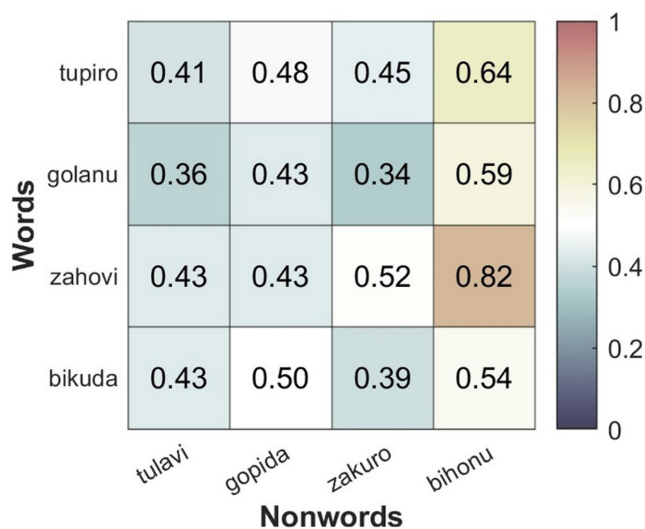


FIGURE 3 Mean correct rates from the familiarity task in each word-nonword pairing. Certain nonwords were easier to reject ('bihonu') than others ('tulavi').

TABLE 1 Mean \pm SD of ITPC in the different frequencies of interest by condition (structured and random).

	Sequence	
	Random	Structured
0.83 Hz (triplet)	0.111 \pm 0.022	0.137 \pm 0.021
1.67 Hz (first harmonic)	0.173 \pm 0.029	0.190 \pm 0.035
2.50 Hz (syllable)	0.423 \pm 0.105	0.436 \pm 0.097

first harmonic of the triplet frequency (1.67 Hz) the statistics showed a tendentious difference ($t(28)=2.023$, $p_{\text{raw}}=.0479$, $p_{\text{corrected}}=.1437$); however, at the syllable

frequency (2.5 Hz) there were no differences between sequences ($t(28)=0.507$, $p_{\text{raw}}=.614$, $p_{\text{corrected}}=1$).

After establishing the effect of the structured stream on the ITPC we examined the ITPC difference distribution on the scalp. Only on the word frequency yielded significant results. We identified the channels sensitive to the word frequency and determined ITPC difference distribution on the scalp. Cluster analysis revealed one significant cluster based on summed t-value ($t_{\text{sum}}=34$, $p<.001$; **Figure 5**) in the frontocentral (F1, F3, F5, FC3, C3, AFz, Fz, F2, F4, F6 F8, FC4, FC2, FCz, Cz, C2, C4) and parieto-occipital regions (TP7, CP5, CP1, P1, P3, P5, P7, P9, Pz, CPz, CP4, CP2, P2, PO4, O2).

Based on the channel cluster shape, we inspected the distribution of raw phase angle values on the scalp. At all time points of the pseudotrials, we found a consistently high phase difference along the antero-posterior axis and decided to split the cluster into a frontocentral and a parieto-occipital cluster, where the border between the clusters was defined as the coronal line determined by the Cz electrode on the scalp. Then, ISPC analysis was performed to test the phase shift between these possible individual clusters. Comparing the coherence of phase angle differences between clusters revealed a higher coherence during the structured sequence (**Figure 6, Left**). In the structured sequence, the average ISPC was 0.110 ± 0.035 while in the random it was 0.093 ± 0.025 . This ISPC difference between the two sequences was statistically significant ($t(28)=2.302$, $p=.029$).

In the second round of ISPC analysis we tested the significance of the measured ISPC values against a permuted population. In the random trials, the mean ISPC was not significantly different from the permuted distribution ($z=-1.119$, $p=.868$), while the difference in the structured sequence reached the 5% significance level ($z=1.772$, $p=.0382$). The ISPC difference of the two sequences was also tested against the difference of the permuted distributions, which was significantly different, as well ($z=2.089$, $p=.0367$, **Figure 6, Right**).

4 | DISCUSSION

The current study showed neural and behavioral evidence that participants were able to acquire visual linguistic statistical regularities from the environment. Participants were presented with written syllables in two sequences: one random and one structured, where syllables followed each other as associated triplets, creating artificial words. The two sequences differed significantly in the detection task during stimulation, resulting in higher detection sensitivity during the structured stream. In addition, the structured sequence was effective in inducing neural entrainment to words, as evidenced by elevated ITPC at

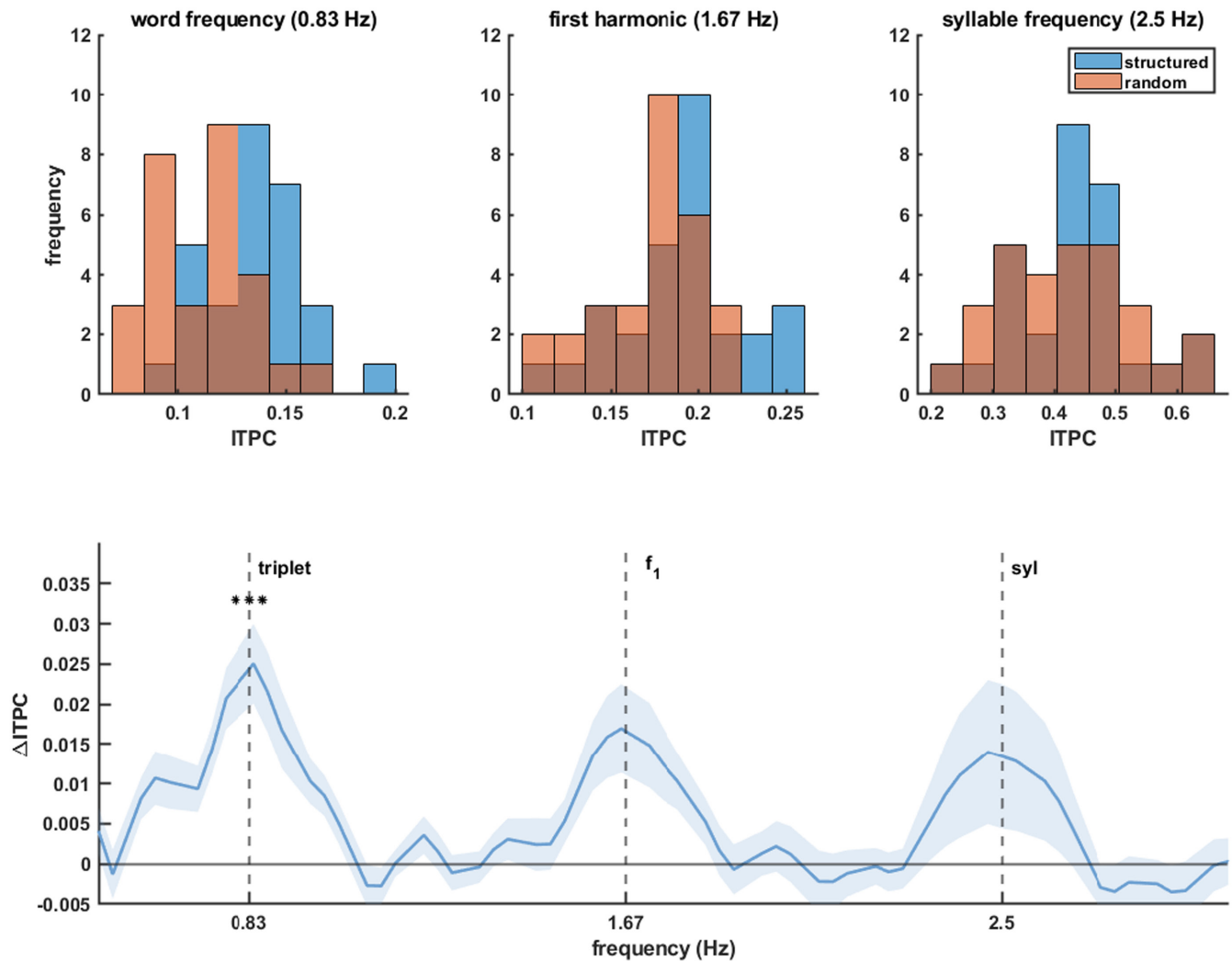


FIGURE 4 Top: The distribution of individual ITPC values in the three frequencies of interest. Bottom: ITPC value differences between the two streams (structured—random) along the frequency spectrum (triplet—triplet frequency, f_1 —first harmonic of the triplet frequency, syl—syllable frequency). Mean values are indicated by the continuous line while the shaded area indicates the standard error of mean. Frequencies of interest are indicated with dashed lines. *** $p_{\text{corrected}} < .001$.

the triplet frequency (0.83 Hz). Importantly, these results emerged in the participants without any instructions or hints to said regularity. After establishing learning, we identified the cortical areas engaged in the process. Observing the scalp distribution of the ITPC difference between sequences revealed a great cluster spanning across frontocentral and parieto-occipital electrode sites. Visual inspection suggested this cluster to be an overlap of two separate clusters, as supported by a subsequent ISPC analysis of phase differences.

4.1 | Behavioral evidence

The behavioral correlates of learning were traced by two tasks: a sequence-irrelevant detection task and an explicit 2AFC familiarity test. The detection task aimed to

maintain attention during stimulation while serving as an implicit indicator of learning. If statistical regularities were acquired in the structured sequence, the repeated syllables would break the structure and result in altered responses compared to the random sequence. The learned structure would also help reduce the false alarm rate by forecasting the upcoming syllables. Importantly, some behavioral differences in the detection task would be expected due to the serial nature of the design (first random, then structured sequence). Thus, other factors, such as fatigue and procedural learning could influence the results. We opted, to maintain this to perform the familiarity test immediately after the structured sequence, similarly to previous research (Henin et al., 2021; Pinto et al., 2022). Nonetheless, in our assessment, the elevated d' values we measured during the structured stream indicate acquisition of the triplet structure. In our case, RT advantages of

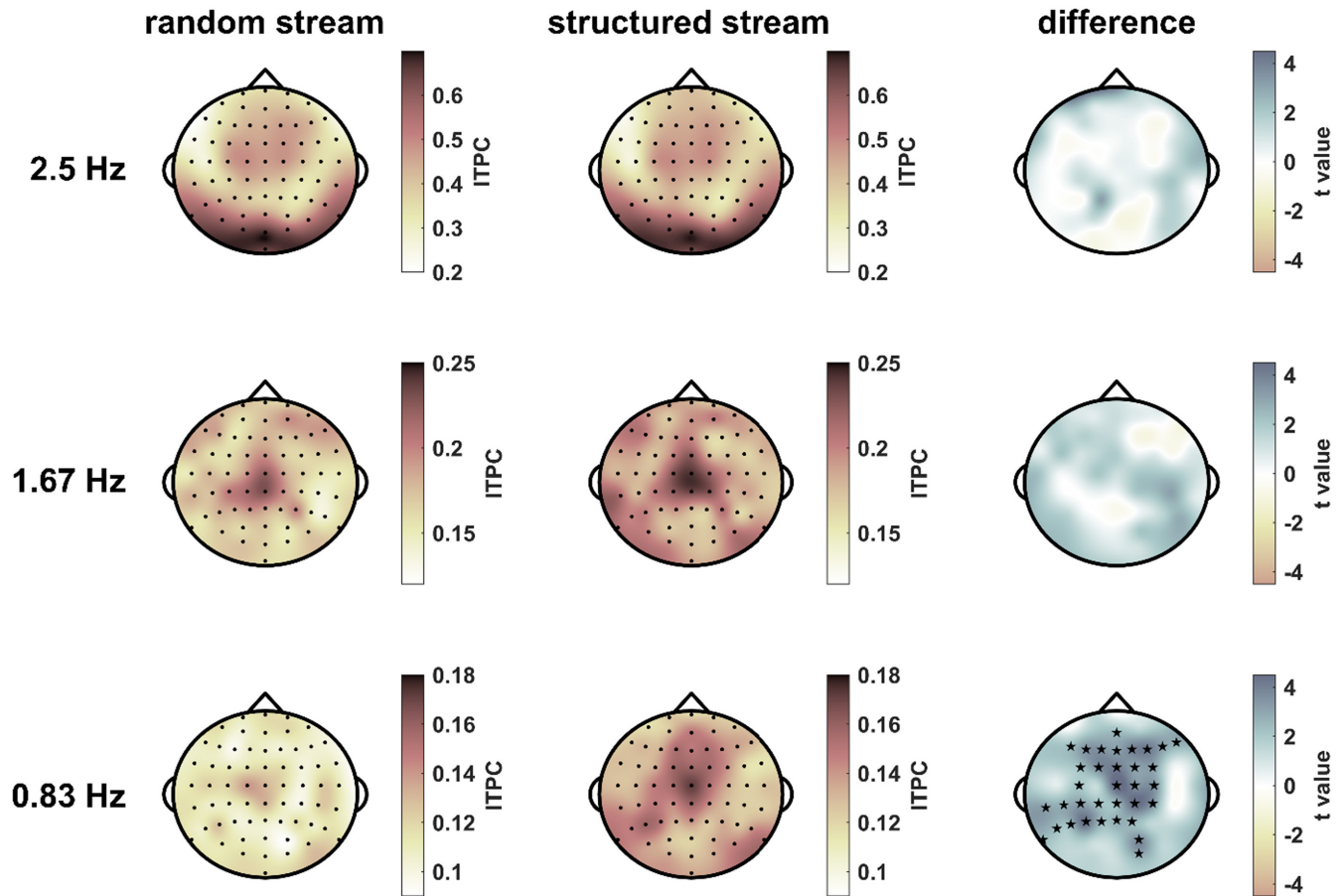


FIGURE 5 ITPC distribution on the scalp in the random (left column) and structured sequence (middle column) in the three frequencies of interest along with the statistical differences between the two streams (right column). Channels in the significant cluster ($p < .001$) are indicated by stars.

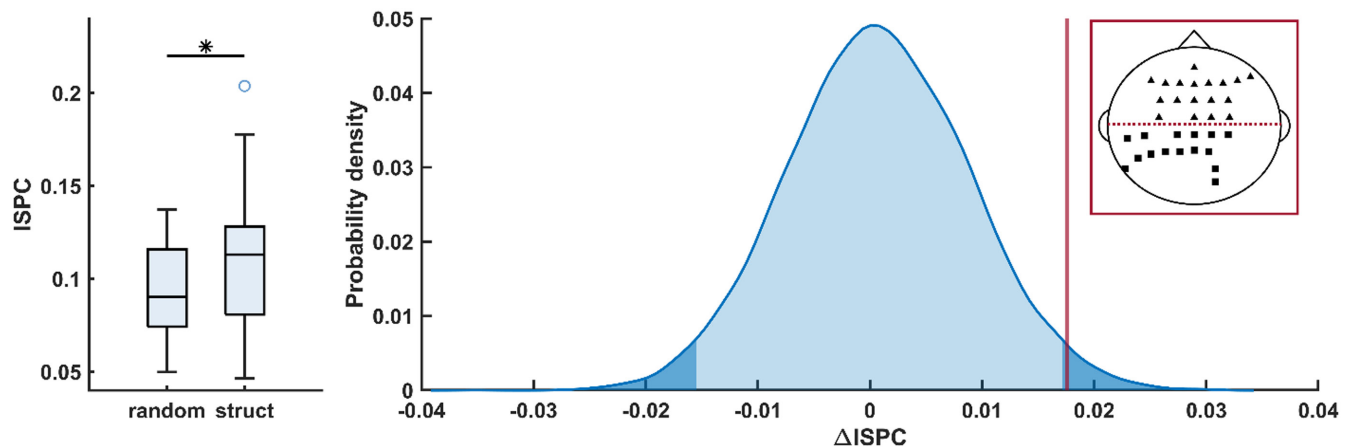


FIGURE 6 Left: Boxplot of triplet frequency ISPC values between the frontocentral and parieto-occipital clusters in the two sequences. $*p < .05$. Right: Probability distribution plot of the ISPC difference of the permuted population, where the shaded areas mark the 2.5 and 97.5 percentiles. The red line indicates the ISPC difference of the anterior and posterior cluster definitions. The scalp distribution and separation of the channels into two cluster can be seen in the topoplot.

triplet-learning (previously reported by Henin et al. (2021) and Pinto et al. (2022)) could have been canceled by fatigue as reported often by participants (data not recorded).

There was no explicit triplet learning detectable by the 2AFC task. However, this may be due to various reasons. First, the stimuli of this familiarity task were derived

from, but not identical to, the stimuli of the presentation phase. During stimulation, each syllable was presented separately, and the only thing holding the triplets together was the TPs within the sequence; in contrast, the syllables were compiled as artificial words (and nonwords) for the familiarity task. This way of testing assumes a considerable amount of abstraction on the participants' behalf. Another important takeaway from the familiarity task was the discrepancy in the performance of some words and nonwords. Although the current dataset is insufficient for an exploratory analysis on this aspect, the subjective familiarity of items appears to be influenced by experience from outside the experimental context. Participants might have evaluated items based on how believable they would be as real (e.g., foreign) words. Please note that familiarity test measure explicit knowledge while this paradigm is assumed to be implicit (Batterink et al., 2015; Kim et al., 2009; Turk-Browne et al., 2005). Additionally, when compared to results from similar learning paradigms (Batterink & Paller, 2017; Bogaerts et al., 2022; Franco et al., 2015; Henin et al., 2021; Pinto et al., 2022; Turk-Browne et al., 2010), this result does not stand out much in being very close to chance performance. The behavioral analyses showed that, although learning was detectable in an implicit task, it does not necessarily transpose to explicit knowledge tested by a familiarity task.

4.2 | Neural entrainment across all channels

Across-channel average ITPC significantly differed between sequences at the triplet frequency (0.83 Hz) but not at the syllable frequency (2.5 Hz). A similar emergence of a phase coherence peak at the frequency of regularity during the structured sequence was already observed across several modalities. Both linguistic (Pinto et al., 2022) and nonlinguistic auditory (Moser et al., 2021) paradigms exerted similar effects using EEG and MEG imaging; comparable results have been observed with nonlinguistic visual stimuli as well (Henin et al., 2021). Surprisingly, some studies found a change in the coherence of the syllable frequency (Batterink & Paller, 2017; Pinto et al., 2022). In such cases, there was an ITPC reduction at the syllable frequency during the structured sequence. This effect was interpreted as a shift toward the word frequency that may disrupt phase coherence at the syllable frequency.

Additional to the above-discussed effects, an ITPC elevation in the harmonics of the 'word' frequency has been previously observed (Batterink & Paller, 2017; Henin et al., 2021; Pinto et al., 2022); studies measuring relative power as a measure of FT routinely sum the effects of the fundamental and harmonic frequencies (Lochy

et al., 2016; Pescuma et al., 2022). In our case, an ITPC peak was detected, but was not significant, at the first harmonic frequency (1.67 Hz). However, as explained by Zhou et al. (2016), these effects at the harmonic frequencies most likely carry no extra information and are a consequence of the waveforms producing neural entrainment.

Although the findings of De Rosa et al. (2022) can be interpreted as a case of SL with written stimuli, their design was based on oddballs with low relative token frequencies. In their case, the frequency tag is based on a periodically appearing surprise signal that emerges as the identity of the rarely occurring items is learned. In our case, however, it is the structure among the items that carries the frequency tag, resulting from the learning of a more complex set of TPs. We thus argue that this is the first case that such type of learning, exemplified by AGL paradigms is detected with FT in a written setting.

4.3 | Scalp distribution of the triplet-related neural activity

Cluster analysis revealed that channels contributing to the observed difference spread across the midline of the scalp with no specific lateralized or anteroposterior dominance. The origin of this great cortical activity resulting in an anterior and posterior channel cluster is not evidenced in the current study considering the limited spatial resolution of the 64-channel EEG. Previously, the following regions have been associated with regularity acquisition in EEG studies: the left anterior and right occipital clusters of Buiatti et al. (2009), the central midline electrodes identified by Batterink and Paller (2017), or the frontocentral areas reported by Pinto et al. (2022).

Beyond EEG's spatial limitations, MEG and ECoG studies tried to further clarify the areas involved in TP acquisition. Auditory nonlinguistic triplet learning has been associated with right temporofrontal areas involving the superior temporal, supramarginal, subcentral, and inferior frontal gyrus identified by MEG recordings (Moser et al., 2021).

In auditory linguistic FT paradigms (Exp. 1., Henin et al., 2021), the superior temporal gyrus, motor cortex, and the pars opercularis were associated with elevated ITPC at both the syllable and word frequencies. Conversely, in the same study, the inferior frontal gyrus, and the anterior temporal lobe only exerted activity at the word frequency. In a visual nonlinguistic paradigm (Exp. 2., Henin et al., 2021), the occipital and parietal regions showed increased ITPC for both the stimulation and regularity frequencies, and ITPC elevation was found in the frontal, parietal, and temporal lobes only at the regularity frequency. Both auditory linguistic and

visual-nonlinguistic modalities exerted effects in the hippocampus as well.

Together with previous research, the anterior channels detected in our study suggests that frontal cortical areas engage in stimulus association, regardless of modality. Similar conclusions have been reached before in SL paradigms utilizing techniques different from FT (Batterink et al., 2019; Conway, 2020; Thothathiri & Rattinger, 2015). Thus, the frontal lobe is a promising candidate as a domain-general hub in probability acquisition. The frontal lobe is involved in many cognitive functions, including the control of attention (Stuss, 2006) and working memory (Thompson-Schill et al., 2002), both strongly correlated with SL (Batterink & Paller, 2019; Janacek & Nemeth, 2013; Lengyel et al., 2021; Musz et al., 2015). Furthermore, the prefrontal cortex (PFC) has rich connections with the hippocampus, another candidate for a domain-general SL center (Fell et al., 2003; Goldman-Rakic et al., 1984). Specifically, the dorsolateral PFC and the inferior frontal gyrus have been associated with SL (Ambrus et al., 2020; Conway, 2020; Nydam et al., 2020; Tóth et al., 2017; Turk-Browne et al., 2009).

We propose that the posterior cluster in our results is a correlate of activity modulation in higher visual networks located near the parieto-occipital sulcus (Karlaftis et al., 2019). This is in line with previous research, showing SL-involvement of high visual centers in the lateral occipital cortex and the inferior temporal gyrus (Turk-Browne et al., 2009), although the latter is not observable with EEG. This theory also agrees with the previous finding that the structure-related activity of the occipital and temporal lobes was only detectable in visual but not in auditory FT learning paradigms (Henin et al., 2021). In conclusion, our posterior cluster is likely a result of modulation in a modality-specific visual network. Importantly, this reasoning does not contradict the domain-general hypothesis, as higher visual networks might be modulated by SL through hippocampal involvement (Bubic et al., 2010). Thus, the posterior activity might be domain-specific, even if originating from a domain-general center.

Alternatively, the posterior cluster could be a correlate of an activity change in the parietal lobe, which suggests that it is a domain-general EEG correlate. The parietal lobe has been reported to be modulated during SL tasks (Forkstam et al., 2006; Skosnik et al., 2002) and it is connected with frontal areas showing modulation in SL (Karlaftis et al., 2019). Moreover, it communicates with the hippocampus and might be modulated by mnemonic processes (Shohamy & Turk-Browne, 2013; Whitlock et al., 2008). This, however, is less likely, as comparable results were only observed in a visual paradigm. The ISPC difference we observed between random and structured conditions provides further evidence of the extended

cortical network. During the random sequence, the phase relationship between the anterior and posterior sites was not more synchronized than what would be expected when picking any combination of channels. Therefore, the IPSC value was not only higher during the structured stimulus sequence, but as the results of the current study suggest, this phase-synchronization between anterior and posterior sites appeared specifically when statistical structure was present in the sequence. Similar connectivity using ISPC has been observed in a task switching paradigm between the frontal and parietal areas (McKewen et al., 2021), but not in any SL paradigms, as far as we are aware.

We would like to emphasize that our EEG-based technique alone has spatial limitations that do not allow for precise localization of the neural activity entrained to the triplet structure. It is clear, however, that the SL-associated activity has a widespread distribution across the scalp, and that this activity appears differently along the antero-posterior axis. Comparing this result with the SL literature—particularly the studies with more definite localizations—we can make assumptions as to where the anterior and posterior activity clusters may originate from but based on the data available, we cannot claim an identity with either of these.

Altogether, our results fit into the wider picture of current SL research. The consistent reappearance of the same frontal region across modalities is promising evidence for the domain general hypothesis, yet the function of this activity remains uncertain. Due to the various roles of the frontal lobe in cognition, it remains unclear which of these contribute to SL. Current papers, including ours, only identified a frontal area without defining its function related to regularity acquisition. We propose that future research should focus on the functional connectivity of SL-related brain regions, to elaborate the roles in the process and define related cortical networks. The addition of a visual linguistic paradigm to the research palette means that generalization of learned structures could be tested and the differences between auditory and visual structure learning pinned down. The written nature of our paradigm could be exploited in linguistic or orthographic processing research as well, exploring the factors that influence the learning of written structures.

5 | CONCLUSION

In the current study, we adapted the FT technique to a linguistic SL paradigm using written syllables as stimuli. Participants showed both behavioral and neural evidence for learning. Further analysis revealed significant differences in neural entrainment only emerging at the

structure frequency. Tracking the distribution of this activity we identified two clusters, showing the involvement of the frontal lobe and parieto-occipital areas during learning. These results are in line with previous research which detected activation of frontal areas with FT in different modalities, both in linguistic and nonlinguistic settings. The adaptation of a linguistic, visual paradigm fills a gap in the neural entrainment literature and extends the research utilities of the FT technique.

AUTHOR CONTRIBUTIONS

Szabolcs Sáringer: Conceptualization; formal analysis; investigation; visualization; writing – original draft. **Péter Kaposvári:** Conceptualization; investigation; writing – review and editing. **András Benyhe:** Conceptualization; formal analysis; investigation; methodology; software; visualization; writing – original draft.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

The datasets analyzed for this study can be found in the Open Science Framework repository (<https://osf.io/brf39>).

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