MedicalXpress

Sentences have their own timing in the brain

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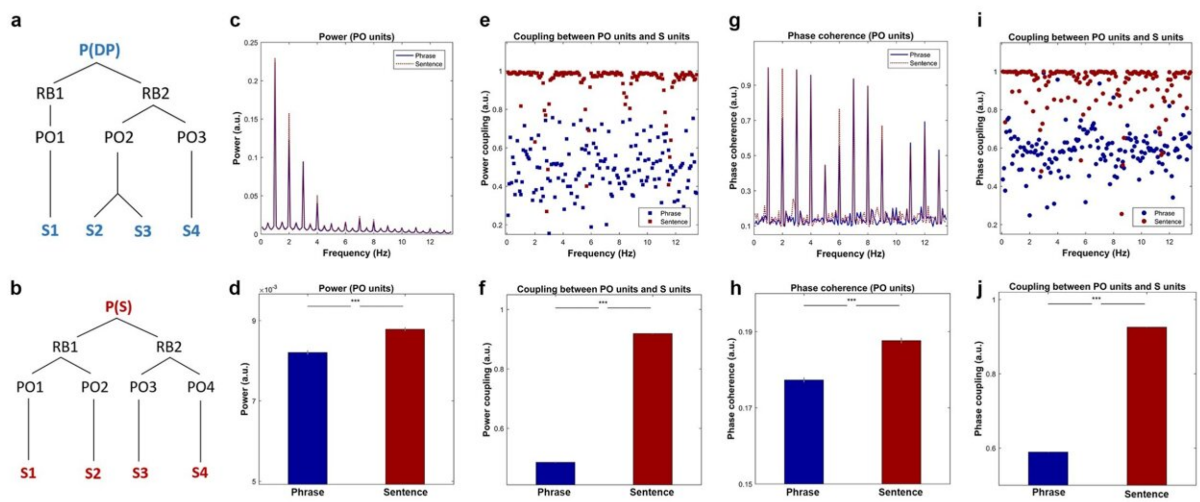


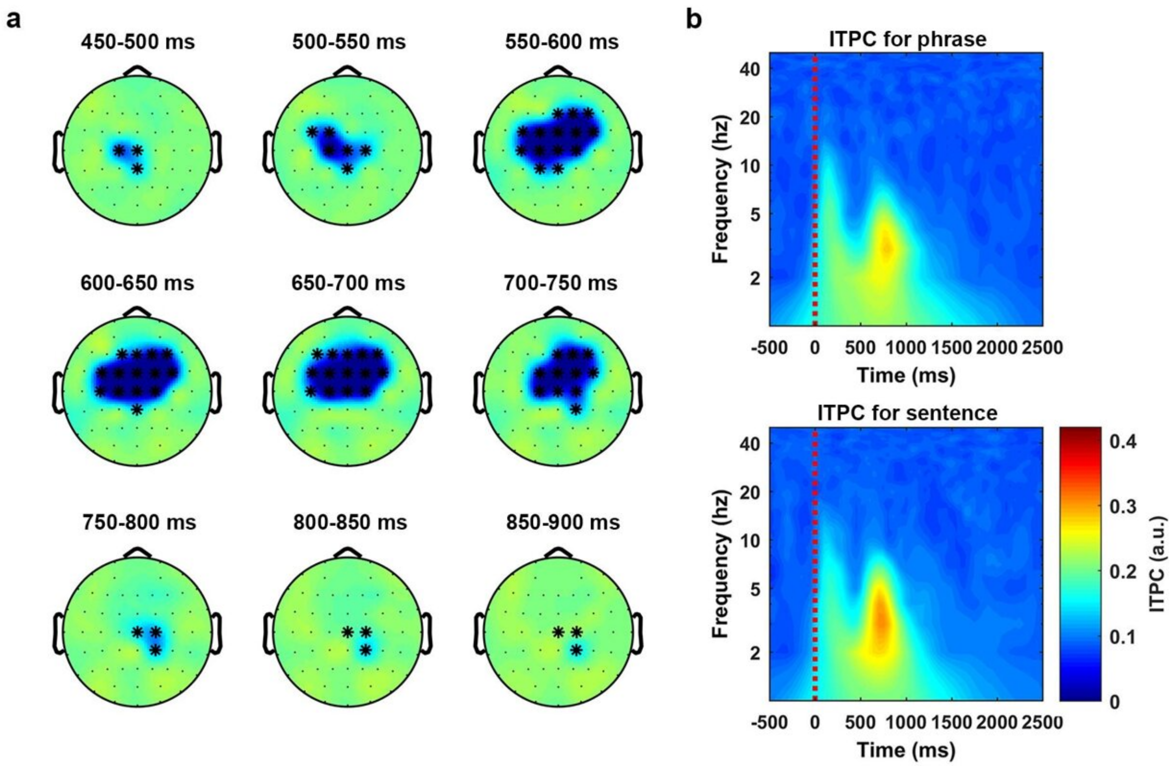
Simulation results based on the time-based binding hypothesis. (a) and (b). The model representation of phrases and sentences, in which the P (Proposition units), RB (Role-filler units), PO (Propositional Object units) and S (syllables units) represent the different types of node in DORA. P(DP) represents the top-level unit is a determiner phase and P(s) represents the highest-level unit is a sentence. (c). Simulation results on power, in which the red dotted line and blue solid line represent the frequency response of the sentences and the phrases, respectively. The shading area covers two s.e.m centered on the mean. (d). Statistical comparison on the frequency combined power using paired sample t-test suggested that the power for the sentences was significantly higher than the phrases (t (99) = 8.40, p

The brain links incoming speech sounds to knowledge of grammar, which is abstract in nature. But how does the brain encode abstract sentence structure? In a neuroimaging study published in *PLOS Biology*, researchers from the Max

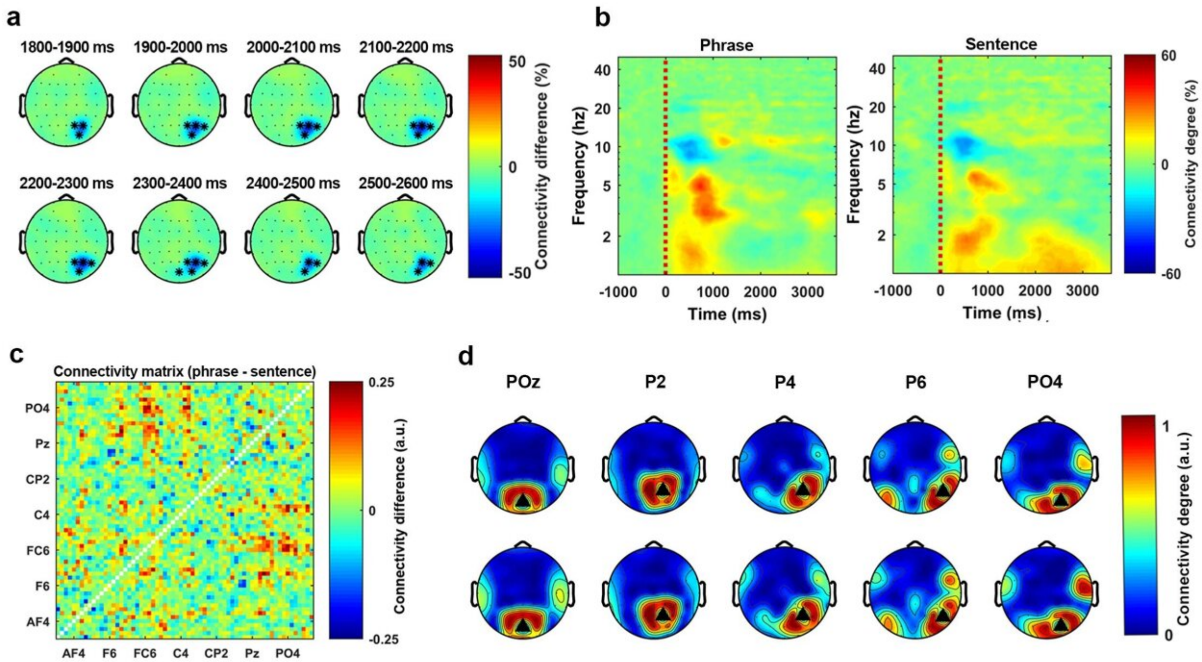
Planck Institute of Psycholinguistics and Radboud University in Nijmegen report that the brain encodes the structure of sentences ("the vase is red") and phrases ("the red vase") into different neural firing patterns.

How does the brain represent sentences? This is one of the fundamental questions in neuroscience, because sentences are an example of abstract structural knowledge that is not directly observable from speech. While all sentences are made up of smaller building blocks, such as words and phrases, not all combinations of words or phrases lead to sentences. In fact, listeners need more than just knowledge of which words occur together: they need abstract knowledge of language structure to understand a sentence. So how does the brain encode the structural relationships that make up a sentence?

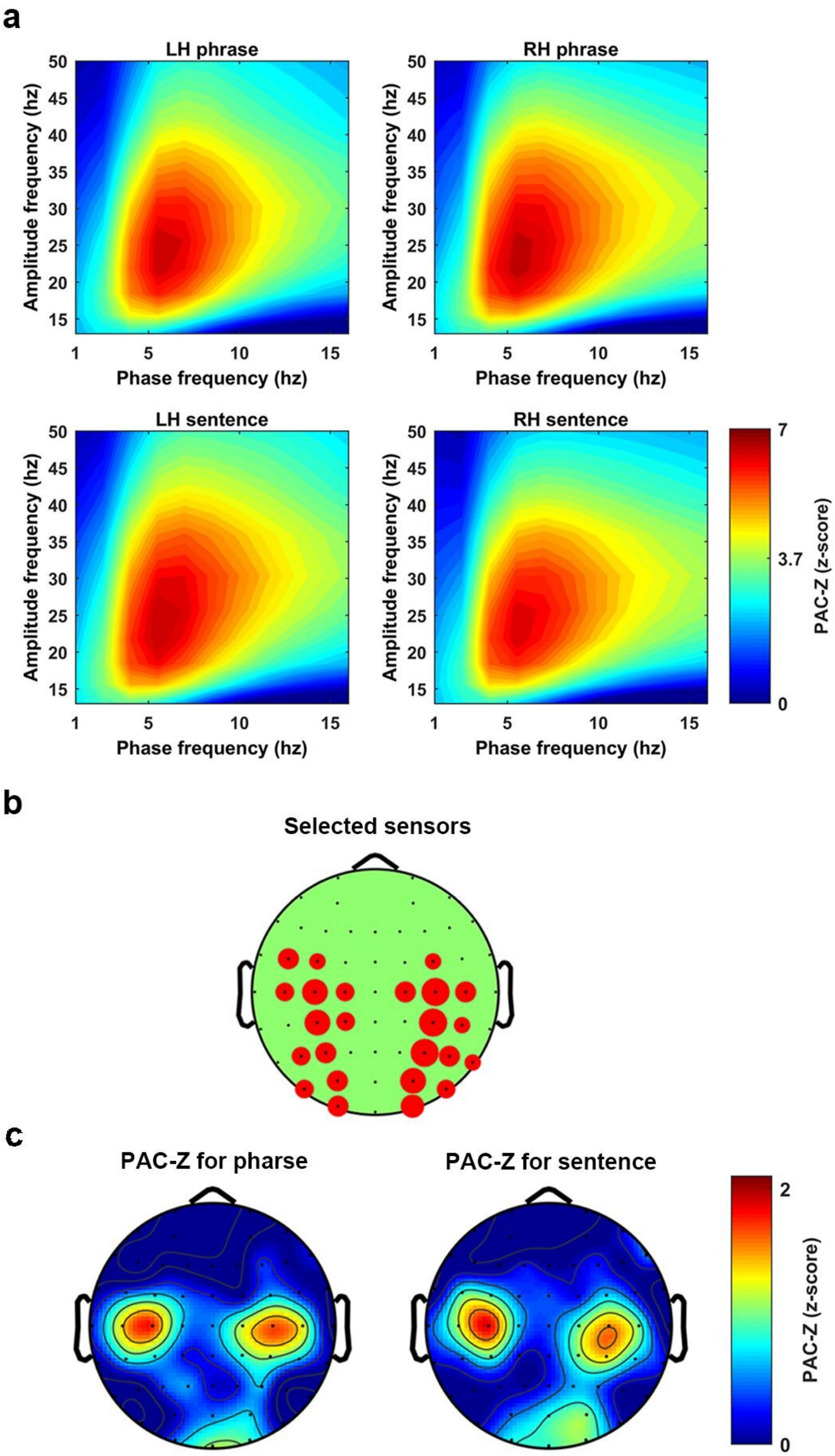
Lise Meitner Group Leader Andrea Martin already had a theory on how the brain computes linguistic structure, based on evidence from computer simulations. To further test this "time-based" model of the structure of language, which was developed together with Leonidas Doumas from the University of Edinburgh, Martin and colleagues used EEG (electroencephalography) to measure neural responses through the scalp. In a collaboration with first author and Ph.D. candidate Fan Bai and MPI director Antje Meyer, she set out to investigate whether the brain responds differently to sentences and phrases, and if this could hint at how the brain encodes abstract structure.



Statistical analysis on the phase coherence (ITPC) was conducted using a non-parametric cluster-based permutation test (1000 times) on a 1200-ms time window, which started at the audio onset and over the frequencies from 2 Hz to 8 Hz. The results indicated that the phase coherence was higher for the sentences than the phrases (p



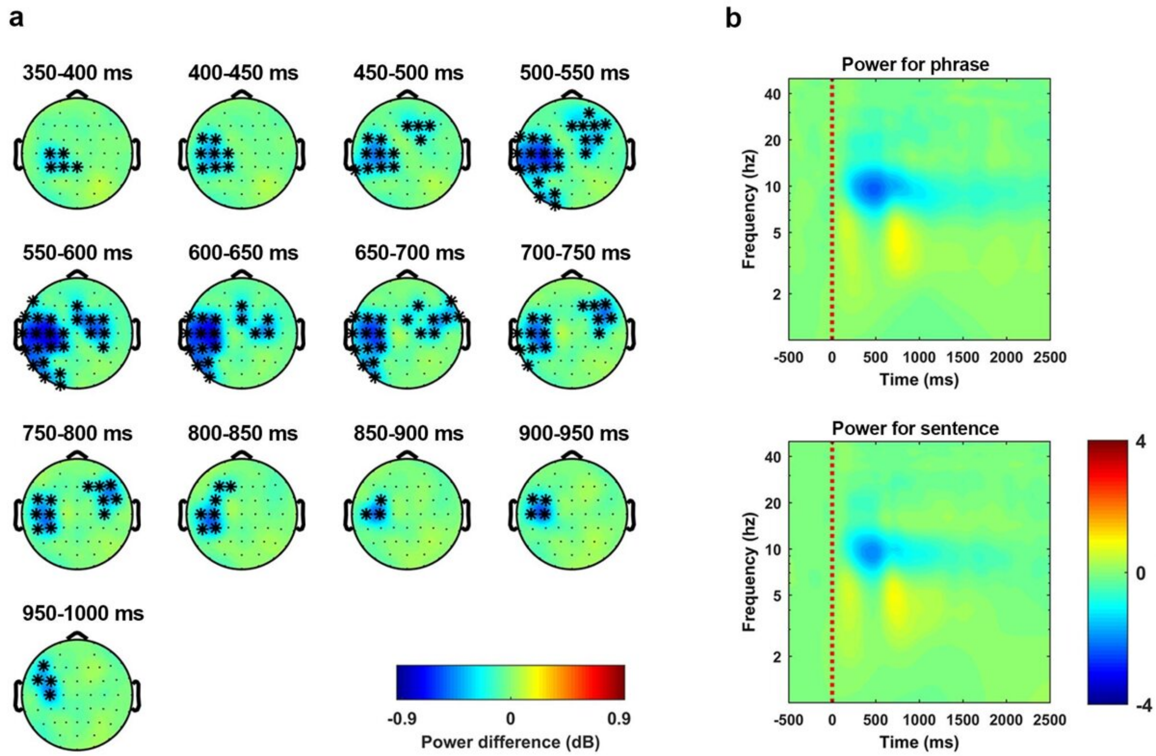
Statistical analysis on the phase connectivity degree was conducted using a non-parametric cluster-based permutation test (1000 times) on a 3500-ms time window, which started at the audio onset and over the frequencies from 1 Hz to 8 Hz. The results indicated that the phase connectivity degree was higher for the sentences than the phrases (p


a
LH phrase
RH phrase
LH sentence
RH sentence
Amplitude frequency (hz)
Phase frequency (hz)
PAC-Z (z-score)
b
Selected sensors
c
PAC-Z for pharse
PAC-Z for sentence
PAC-Z (z-score)

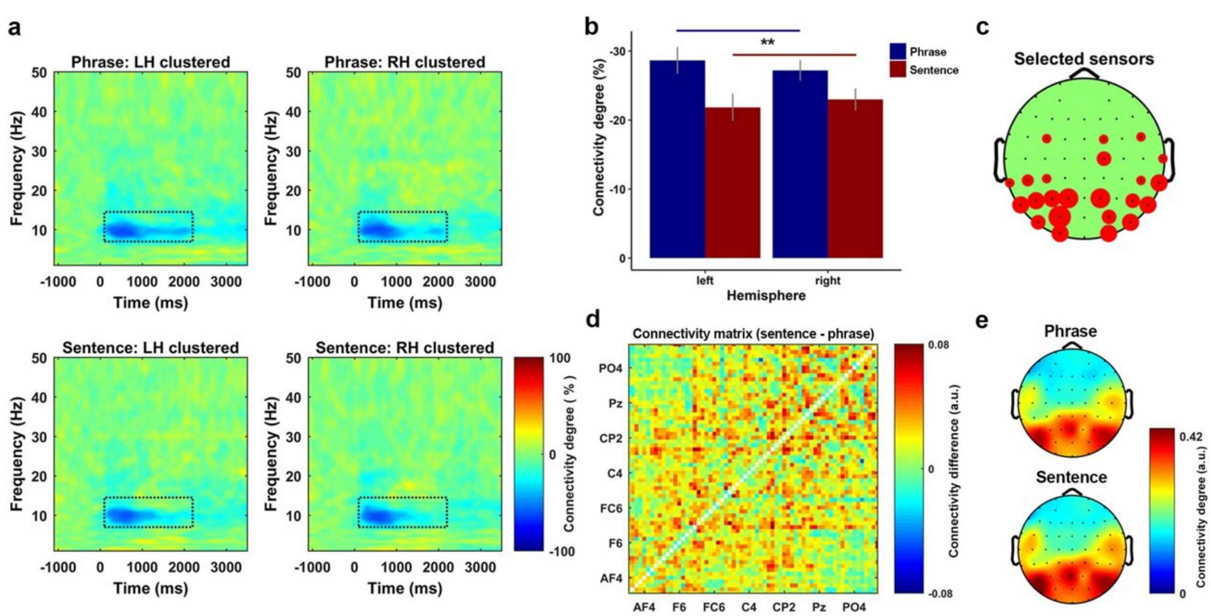
The figure shows a z-score transformed phase amplitude coupling, PAC-Z. (a) The PAC-Z for the phrases and the sentences at each hemisphere. Each figure was created by averaging 8 sensors which showed the biggest PAC-Z over the ROI. A z-score transformation with Bonferroni correction was conducted to test the significance, which lead to the threshold to be 3.73 corresponding to p-value equals 0.05. (b) The figure shows how sensors were selected at each hemisphere. The bigger the red circle indicates the more times this sensor was selected across participants. (c) The topographical distribution of the PAC-Z, which indicates the PAC was largely localized at the bilateral central areas. The underlying data can be found in https://doi.org/10.5281/zenodo.6595789. Credit: Fan Bai, Antje S. Meyer and Andrea E. Martin

The researchers created sets of spoken Dutch phrases (such as "de rode vaas," "the red vase") and sentences (such as "de vaas is rood," "the vase is red"), which were identical in duration and number of syllables, and highly similar in meaning. They also created pictures with objects (such as a vase) in five different colors. Fifteen adult native speakers of Dutch participated in the experiment. For each spoken stimulus, they were asked to perform one of three tasks in random order. The first task was structure-related, as participants had to decide whether they had heard a phrase or a sentence by pushing a button. The second and third task were meaning-related, as participants had to decide whether the color or object of the spoken stimulus matched the picture that followed.

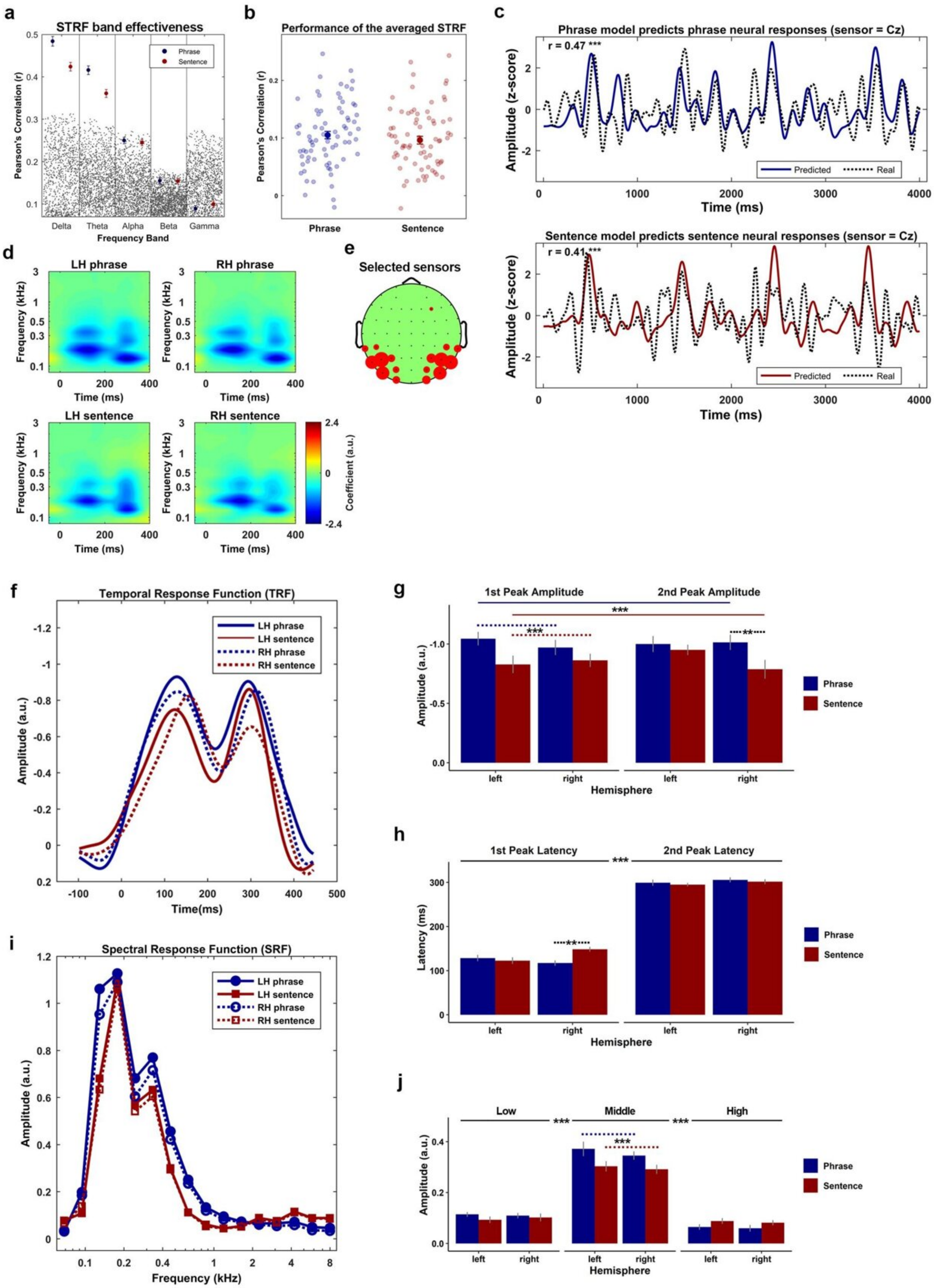
As expected from computational simulations, the activation patterns of neurons in the brain were different for phrases and sentences, in terms of both timing and strength of neural connections. "Our findings show how the brain separates speech into linguistic structure by using the timing and connectivity of neural firing patterns. These signals from the brain provide a novel basis for future research on how our brains create language," says Martin.



Statistical analysis on the induced activity was conducted using a non-parametric cluster-based permutation test (1000 times) on a 1000-ms time window, which started at the audio onset and over the frequencies from 7.5 Hz to 13.5 Hz. The results indicated that the phase coherence was higher for sentences than phrases (p



Power connectivity degree for all conditions. Each plot was clustered by the sensors at each hemisphere that showed the biggest inhibition on the grand averaged power connectivity. (b) The results of a two-way repeated measure ANOVA for the power connectivity on the factors of stimulus-type (phrase or sentence) and hemisphere (left or right). The results indicate a significant main effect of stimulus-type, post hoc comparison on the main effect indicated that the overall inhibition level of the power connectivity was stronger for the phrases than the sentences ($t(29) = 2.82$, $p = 0.0085$ **, two-sided). (c) How sensors were selected for the clustering. The bigger the red circle indicates the more times the sensor was selected across participants. (d) The connectivity differences between the phrases and the sentences on all sensor-pair. The figure was drawn using the average of the binarized connectivity matrix of the sentences minus the matrix of the phrases. The results indicate that the connectivity degree over the sensor space for the sentences was higher than the phrases. (e) Topographical representation of the binarized connectivity, which was clustered using the sensors showed biggest inhibition on the power connectivity. The upper and lower panel shows the phrase and sentence condition, respectively. The underlying data can be found in https://doi.org/10.5281/zenodo.6595789. Credit: Fan Bai, Antje S. Meyer and Andrea E. Martin


a
STRF band effectiveness
Pearson's Correlation (r)
Phrase
Sentence
Delta
Theta
Alpha
Beta
Gamma
Frequency Band
b
Performance of the averaged STRF
Pearson's Correlation (r)
Phrase
Sentence
c
Phrase model predicts phrase neural responses (sensor = Cz)
r = 0.47 ***
Amplitude (z-score)
Predicted
Real
Time (ms)
Sentence model predicts sentence neural responses (sensor = Cz)
r = 0.41 ***
Amplitude (z-score)
Predicted
Real
Time (ms)
d
LH phrase
RH phrase
LH sentence
RH sentence
Frequency (kHz)
Time (ms)
Coefficient (a.u.)
e
Selected sensors
f
Temporal Response Function (TRF)
LH phrase
LH sentence
RH phrase
RH sentence
Amplitude (a.u.)
Time(ms)
g
1st Peak Amplitude
2nd Peak Amplitude
Amplitude (a.u.)
Phrase
Sentence
left
right
Hemisphere
h
1st Peak Latency
2nd Peak Latency
Latency (ms)
Phrase
Sentence
left
right
Hemisphere
i
Spectral Response Function (SRF)
LH phrase
LH sentence
RH phrase
RH sentence
Amplitude (a.u.)
Frequency (kHz)
j
Low
Middle
High
Amplitude (a.u.)
Phrase
Sentence
left
right
Hemisphere

Comparison between the real performance and the random performance of the STRF in each canonical frequency band. The results suggested that only the performance of the STRF in the Delta band (< 4 Hz) and Theta band (4-8 Hz) was statistically better than the random performance. The blue and red dots represent the real performance of the STRFs for the phrases and the sentences, respectively. The error bar represents two s.e.m centered on the mean. The gray dots represent the random performance drawn by permutations. (b) The performance of the low-frequency range (< 8 Hz) STRF averaged across all participants. The solid blue and red dot represent the averaged performance across all testing trials. The error bar represents two s.e.m across the mean. The transparent blue and red dots represent the model's performance on each testing trial for the phrases and the sentences, respectively. The results indicate no performance difference on the kernel between the phrases and the sentences. (c) The comparison between the real neural response (dashed lines) and the model predicted response (solid blue for the phrase, solid red for the sentence) at a sample sensor Cz. The results suggest that the STRFs performed equally well for the phrases (r = 0.47, p