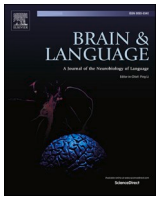
Brain & Language 282 (2026) 105847



Contents lists available at ScienceDirect

Brain and Language

journal homepage: www.elsevier.com/locate/b&l



Research Article



A shared EEG signal for the maintenance of visually and linguistically evoked objects: theta-gamma phase-amplitude coupling

Wesley Leong [a,b,*], Gerry T.M. Altmann [a,b]

[a] University of Connecticut, Storrs, CT, USA
[b] Connecticut Institute for the Brain and Cognitive Sciences, Storrs, CT, USA

ARTICLE INFO

Keywords:
Phase-amplitude coupling
Visual working memory
Sentence comprehension
Object states
Event cognition

ABSTRACT

How do our brains represent events in language? Recent work has shown that when we comprehend state-change events, multiple representations corresponding to different states of an object are simultaneously activated. As the sentence unfolds and the object is cued for retrieval, areas of the brain associated with representational conflict show greater activation in proportion to how dissimilar the object-states are to each other. Before being retrieved, however, these object-states have to be actively maintained in the brain. What are the neural mechanisms by which we do so? Across two EEG experiments, we present evidence that, during sentence processing, the maintenance of multiple object-states in state-change events is supported by a neural signal that has been frequently linked to visual working memory: left temporal theta-gamma phase-amplitude coupling.

1. Introduction

What do our minds represent when we comprehend state-change events in language? Consider the sentence: "The chef will weigh the onion, and then he will smell it". Throughout the event described by the sentence, the onion goes through a series of states that are perceptually and functionally indistinguishable from each other. Essentially, the onion does not change its intrinsic state in either the weighing or smelling events. We might refer to this as a sentence where the object undergoes "minimal change". Contrast that with a sentence like "the chef will *chop* the onion, and then he will smell it". Here, the onion undergoes "substantial change", such that the onion at the beginning and at the end of the chopping event is in two distinct states–its intact state and its chopped state. When the onion is referenced again later, at the sentence-final "it", we need to retrieve the appropriate state. This process of selecting between competing representations of the same object token has been shown, using fMRI, to elicit a brain response that is sensitive to conflict (Hindy et al., 2012; Solomon et al., 2015). Activity in the left posterior ventrolateral prefrontal cortex (left pVLPFC), an area that preferentially responds to incongruent trials in the Stroop task, also shows more activation in sentences where there is substantial change to the object (Hindy et al., 2012; Solomon et al., 2015); importantly, the degree of left pVLPFC activation correlates with the degree of object change (Hindy et al., 2012). Just as conflict in the Stroop task arises due to competition between mutually exclusive color representations bound to the same object (Curtis et al., 2024), so does competition between *dissimilar* object-states that are bound to the same token in a substantial change event. Furthermore, this competition is dependent on the changed object being cued for retrieval. Solomon et al. (2015) showed that the VLPFC effect for chop/weigh type sentences only occurs when the same object token was referenced ("the chef will chop the onion, and then he will smell the onion"). When a different token of the same type was introduced instead ("[…] smell another onion"), the VLPFC did *not* preferentially activate to either sentence type.

One might wonder why there is a need to maintain multiple object-states in the first place. For example, a comprehender could simply hold the most recent state (e.g., the chopped onion) in mind under the assumption of iconicity: that the linear unfolding of events in language mirrors their unfolding in time (Hopper, 1979). There are two reasons to reject such a proposal. First, if one did not maintain some representation of the initial state, how could one know that an event had occurred? Second, that assumption does not always hold. In the example above, the state of the onion that should be retrieved also happens to be the most recent state. However, if the sentence had instead proceeded as: "the chef will chop the onion, but first he will smell it", one would have to retrieve the intact onion instead. Indeed, Hindy et al. (2012) found no activation difference between "and then" and "but first" type sentences. Regardless of the temporal context, sentences with substantial change to

* Corresponding author at: University of Connecticut, Storrs, CT, USA.
E-mail address: wesley.leong@uconn.edu (W. Leong).

https://doi.org/10.1016/j.bandl.2026.105847
Received 3 December 2025; Received in revised form 18 September 2026; Accepted 21 September 2026
Available online 25 September 2026
0093-934X/© 2026 Elsevier Inc. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

the object engendered more conflict in the brain than those with minimal change. Among other reasons, uncertainty about the upcoming input necessitates that we maintain, minimally, the initial and end states of the onion simultaneously in memory–when the object is cued again, we select among its previous states for integration into our mental models as the language unfolds.

Prior to the selection of a given object-state, the representations need to be maintained in parallel in the mind. What are the neural dynamics by which we do this? We hypothesize that the brain leverages the same neural mechanisms it uses to hold objects and their features in visual working memory. This proposal shares similarities with embodied theories of cognition, which contend that the mental representations of objects are grounded in our sensorimotor systems (Barsalou, 2008; Barsalou et al., 2003). Indeed, there is experimental evidence of this. For example, Lee et al. (2012) showed that the neural resources for mental imagery of objects elicited through language overlap with those used in visual perception. In the study highlighted earlier, Solomon et al. (2015) found increased connectivity between left pVLPFC and *visual cortex* when the same object token was referenced again ("the chef will chop the onion, and then he will smell the onion"). Going a step further, Hindy et al. (2015) showed that the mental imagery of object state change also recruits visual cortical areas. In an fMRI study, they displayed images of objects (e.g., a balloon) to participants and prompted them (via *written* sentences) to imagine these objects undergoing changes of state (e.g., "inflate the balloon"). The results showed a correlation between degree of change to the object and dissimilarity in visual cortical activation patterns. The more dramatic the change, the more dissimilar the patterns were, suggesting that the two distinct states of the object were represented in visual areas. Furthermore, visual cortical dissimilarity predicted activation in the left pVLPFC, the Stroop-sensitive neural region previously observed to preferentially activate when substantially-changed objects are cued for retrieval in language (Hindy et al., 2015). One might thus predict that, beyond perception, the same neural processes used to *maintain* one or more visually-perceived objects in working memory may likewise be used to hold one or more linguistically-elicited object-states in the mind.

What form might these neural processes take? One candidate signal is theta-gamma phase-amplitude coupling in left temporal regions (henceforth referred to as TG-PAC). TG-PAC is characterized as the modulation of a high-frequency wave's amplitude (>25 Hz gamma) by the phase of a low-frequency oscillation (4–8 Hz theta), such that the amplitude of the fast wave waxes and wanes with the phase of the slower wave. Functionally, TG-PAC has been strongly linked to working memory processes (e.g., Chaieb et al., 2015; Tamura et al., 2017). In humans, it has been repeatedly observed to increase with visual working memory load (Axmacher et al., 2010; Bahramisharif et al., 2018; Canolty et al., 2006; Chaieb et al., 2015; Daume et al., 2024; Heusser et al., 2016; Rajji et al., 2017) and performance (Daume et al., 2024; Holz et al., 2010; Reinhart & Nguyen, 2019; Rutishauser et al., 2010; Sauseng et al., 2009), pointing to its strong functional role in working memory processes. While some of these studies localized TG-PAC to the hippocampus (e.g., Axmacher et al., 2010; Daume et al., 2024), others have shown it to be detectable at extracranial electrodes (Fig. 1; Daume et al., 2017; Reinhart & Nguyen, 2019), allowing its investigation using surface EEG.

What is the functional role of TG-PAC? Here we highlight one hypothesis which is particularly relevant for maintaining object-states in language: that TG-PAC reflects a neural code that conveys information about multiple items maintained sequentially in working memory (Fell & Axmacher, 2011; Jensen & Lisman, 2005; Lisman, 2005; Lisman & Buzsáki, 2008; Lisman & Idiart, 1995; Roux & Uhlhaas, 2014 for review). Under this framework, the individual gamma oscillations nestled within a larger theta wave reflect the items encoded in working memory. This builds on previous work showing that theta oscillations accompany increased integration of perceptual representations in memory (Clouter et al., 2017; Köster et al., 2019), and gamma oscillations reflect the

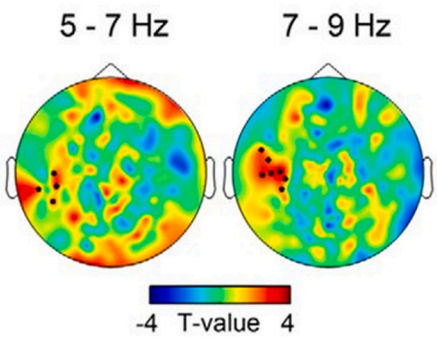


Fig. 1. Topography of the sensor-level TG-PAC effect in MEG identified by Daume et al. (2017); figure reproduced without modifications under a CC-BY license. Reinhart and Nguyen (2019) found a topographically similar cluster in EEG, which we do not have permission to reproduce as a figure.

encoding of individual items (Kaiser et al., 2008; Roux et al., 2012). They reflect the summed activity of neural populations that together form the representational basis for these items; the theta wave in turn is an envelope reflecting the organization of these items in sequence as an ensemble. In particular, theta-gamma coupling has been implicated in the associative binding of visual perceptual features (Köster et al., 2018)–by extension, it might reflect the binding of multiple features to the same object. The evidence thus provides the theoretical grounding for TG-PAC as reflecting domain-general representational content in working memory. As such, we hypothesize that the representational capabilities afforded by TG-PAC may also subserve our ability to represent and maintain multiple object-states bound to a single object token in language. We are theoretically agnostic with respect to whether, in the domain of cognitive processes, neural oscillations more generally, and TG-PAC more specifically, simply *reflect* representational content or in fact *convey* that content.

What differences in TG-PAC might we expect as a function of the amount of change to the objects? As discussed above, the pattern of fMRI findings contrasting substantial and minimal change sentences (Hindy et al., 2012, 2015; Solomon et al., 2015) suggests that retrieving the appropriate object-state is harder when the states are more dissimilar to each other. One might thus expect that the representational demands of *maintaining* these object-states in memory, prior to their being cued for retrieval, differs as a function of their dissimilarity as well. If the object-states are similar to one another, representing them simultaneously might be easier due to featural overlap between the states. In contrast, sentences with substantial change to the object might incur a greater maintenance cost to represent the distinct features of the dissimilar object-states. Consequently, the strength of TG-PAC might be greater for sentences in which the object changes substantially.

This paper presents two experiments testing the hypothesis that TG-PAC is greater for sentences containing substantial change to the object. The first is a re-analysis of previously collected EEG data aggregated across three different sentence processing experiments. These experiments all included sentences with the minimal/substantial change contrast ("the chef will weigh/chop the onion") described above. This reanalysis yielded a cluster of left-temporal electrodes showing increased TG-PAC for substantial-change sentences (with a similar topology as previously reported in visual working memory studies, e.g., Daume et al., 2017; Reinhart & Nguyen, 2019). A second experiment identified a TG-PAC cluster using a visual working memory task, as previously reported for visual working memory (Daume et al., 2017; Reinhart & Nguyen, 2019) and used this cluster as a localizer to restrict our analysis with substantial and minimal change sentences.

2. Experiment 1

2.1. Methods

2.1.1. Participants

We aggregated the data from 3 prior EEG studies (two of which were part of master's/doctoral theses; Ekves, 2022; Prystauka, 2018) for analysis as Experiment 1. These studies had been designed to explore event-related potentials associated with change-of-state sentences of the kind described above. In total, seventy-nine healthy right-handed adults (the age and gender information for these participants is unavailable due to data loss) had participated in these studies for either course credit or monetary compensation (at a rate of $10/h). All participants had reported normal or corrected-to-normal vision and no history of psychiatric or neurological disorders. The experiment protocol had been approved by the University of Connecticut Institutional Review Board. Participants had given their informed written consent before participating in these studies.

2.1.2. Experiment design

Participants had been asked to read a series of sentences on a screen and periodically answer yes/no questions about those sentences while their EEG data was recorded. Stimuli were presented word-by-word, centered on the screen (Fig. 2, top). Each word was displayed for 300 ms and followed by a blank screen for 300 ms, for a total of 600 ms between the onset of each word. In the first sentence, an object underwent either substantial or minimal change (Table 1). In the second sentence, it was referenced again either as a repeated noun phrase ("the onion") or a pronoun ("it"). Sentences were created in pairs such that only the verb changed to denote substantial or minimal change to the object (e.g., "the chef will weigh/chop the onion, and then he will smell the onion/it"). These minimally different pairs were counterbalanced across subjects such that each participant read only one sentence from each pair. For the current analyses we collapsed across the type of reference (full noun phrase vs. pronoun) such that there were 80 trials in each condition, for a total of 160 experimental trials per subject. The three experiments each contained other sentences in their respective task designs, but these were excluded from the present analysis.

Table 1
Example stimuli.

Degree of change	Example trial
Minimal	The chef will weigh the onion. And then, he will smell the onion/it.
Substantial	The chef will chop the onion. And then, he will smell the onion/it.

2.1.3. EEG

EEG was recorded using 256-channel EGI HydroCel Geodesic Sensor Nets at a sampling rate of either 250 Hz or 1000 Hz across the three studies, with the online reference at Cz. EEG data was preprocessed and analyzed in version 1.7 of the MNE-Python package (Gramfort et al., 2013) and Python 3.10.6. Facial channels were dropped before preprocessing (64 channels) and the signal was re-referenced to the mean of the remaining channels. A copy of the raw signal was created and bandpass filtered at 1–80 Hz. Epochs were then extracted from 1.8 s–7.2 s from onset of the first word (corresponding to the onset of the critical

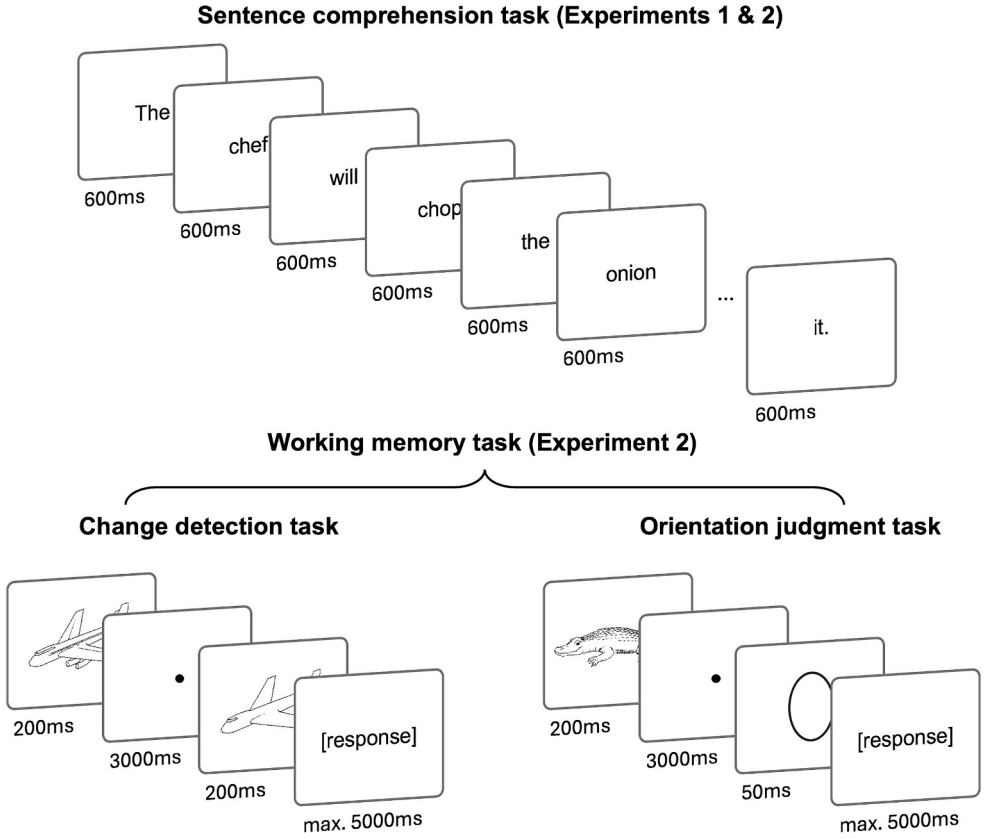


Fig. 2. Visualization of task flow. **Top:** Sentence comprehension task in Experiments 1 and 2. Words were sequentially presented every 600 ms (300 ms on, 300 ms off). Occasionally, a yes/no comprehension question followed (not depicted). **Bottom:** Working memory task in Experiment 2. Left: Change detection task: A line drawing was shown for 200 ms, followed by a 3000 ms retention period, then a prompt for 200 ms. Participants responded if the images were the same or different. Right: Orientation judgment task. A line drawing was shown for 200 ms, followed by a 3000 ms delay, then an ellipse for 50 ms. Participants responded if the ellipse was oriented vertically or horizontally.

verb until the end of the sentence) and downsampled to 250 Hz. Epochs with large artifacts were visually identified, marked, and excluded from independent component analysis (ICA). An ICA was fit to the remaining epochs, and components containing blinks, eye movements, and muscle artifacts were visually identified and selected for removal. The fitted ICA was then applied to the epoched data filtered at 0.1–80 Hz. Finally, epochs exceeding a peak-to-peak threshold of 300 μV were discarded before analysis. These steps are in line with the best practices as suggested in the MNE-Python documentation (Larson et al., 2024). On average, 73.8 ± 8.1 trials in the substantial change condition and 73.8 ± 8.4 in the minimal change condition were retained for each subject.

2.1.4. Phase-amplitude coupling

TG-PAC was estimated using a non-linear driven autoregressive model (DAR), implemented via the pactools package in Python (Dupré la Tour et al., 2017). We summarize here the basic characteristics of this method, but refer the reader to the original paper for a more in-depth technical discussion of the details. Notably, DAR models offer some advantages over more traditional methods of calculating PAC. For instance, they are more robust for short data samples and can capture how the amplitude of the slow oscillation affects coupling strength–a component that other PAC metrics often disregard (Dupré la Tour et al., 2017). Furthermore, they avoid pitfalls stemming from assumptions about the range and bandwidth of coupled frequencies that other methods, particularly those that use the Hilbert transform, are susceptible to (Berman et al., 2012; Chavez et al., 2006; Dvorak & Fenton, 2014; Hyafil, 2015; Seymour et al., 2017).

In brief, DAR models use model likelihood as a goodness-of-fit criterion for characterizing phase-amplitude coupling. In contrast to many traditional methods of calculating PAC (e.g., the Modulation Index; Tort et al., 2010), which extract and compute features for all phase and amplitude frequencies, DAR models are *generative*: they fit a single autoregressive model to the data, modelling the full spectrum of amplitude frequencies as some polynomial function of a driving signal (in this case, the phase-frequency wave). The driving signal is first obtained by bandpass filtering the raw signal around a specified frequency (e.g., our low frequency wave of interest); this driving signal is then subtracted from the raw signal, yielding a residual signal which contains the high frequencies of interest. The autoregressive model is fit to this residual, yielding a power spectral density of the residual signal that is *conditional* on the driver's value. The results of the DAR model are then converted into a PAC metric by first normalizing the conditional PSD at each amplitude frequency into a probability distribution (across driver phases), then calculating its log-normalized Kullback-Leibler divergence against a uniform distribution.

In line with sensor-space TG-PAC effects previously (Daume et al., 2017; Reinhart & Nguyen, 2019), we restricted our analysis to phase frequencies between 3 and 12 Hz (in 1 Hz increments, with a bandwidth of 2 Hz) and amplitude frequencies in the 18–50 Hz range (in 2 Hz steps). This yielded a comodulogram of phase and amplitude frequencies showing the strength of coupling between those frequencies for each condition, channel, and subject. A difference score was then calculated between conditions for each subject, and the resulting difference array was submitted to a cluster-based permutation test (Maris & Oostenveld, 2007). Points falling below an uncorrected p-value of 0.05 were grouped into clusters by adjacency along the dimensions of phase frequency, amplitude frequency, and sensor location. As such, points within the cluster comprised phase-amplitude coupling values for a given phase frequency, amplitude frequency, and channel. Cluster size was calculated as the sum of t-values at each point within the cluster.

2.2. Results

The within-subjects cluster identification procedure revealed a cluster of electrodes in the left temporal region (Fig. 3A), spanning frequencies in the theta-alpha bands (3–12 Hz) and gamma band (32–50 Hz), that showed increased TG-PAC for substantial-change sentences compared to minimal-change sentences (Fig. 3B). This cluster was the largest of those identified, but did not reach statistical significance in the cluster-based permutation test ($p = 0.67$). The cluster spanned electrodes 58, 64, 65, 66, 70, 71, 72, 74, 75, 76, 77, 78, 83, and 84 of the 256-channel HydroCel GSN.

2.3. Discussion

We observed a cluster of left temporal electrodes which individually exhibited increased TG-PAC for substantial compared to minimal change sentences. Notably, the topography of this cluster appeared to match the visual working memory effects found elsewhere (e.g., Daume et al., 2017; Reinhart & Nguyen, 2019). However, because the cluster as a whole did not reach statistical significance in a permutation test, the results were inconclusive. Note that since cluster identification and cluster permutation (the hypothesis test) are two independent processes, we interpret Experiment 1 as providing preliminary evidence that the

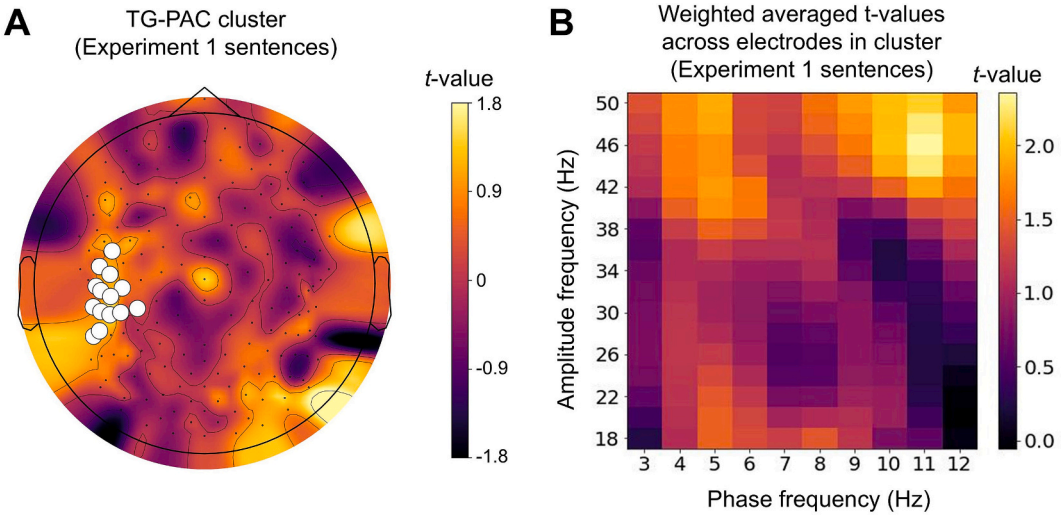


Fig. 3. TG-PAC results for Experiment 1. **A:** Experiment 1: Largest cluster of TG-PAC difference between substantial and minimal change sentences (white dots mark channels within the cluster). **B:** Comodulogram showing t-values averaged across channels, weighted by the number of cells from each channel within the cluster, for each phase-amplitude frequency pair.

effect found by Daume et al. (2017) and Reinhart and Nguyen (2019) may be present between substantial and minimal change sentences, despite the failure to reach statistical significance across all of sensor space. This was likely not due to low sample size ($N = 79$) but may have been due to a number of factors affecting statistical power. One possibility is that whereas Daume et al. (2017) and Reinhart and Nguyen (2019) contrasted different tasks, we contrasted different *conditions* of the same sentence comprehension task. Given that cluster-based permutation tests have limited sensitivity to detect focal effects (Groppe et al., 2011), we may have failed to detect relatively subtle differences in TG-PAC owing to the minor changes between sentences. Given these limitations, we designed a follow-up experiment in which we added a visual working memory task, which has been shown to elicit TG-PAC (Daume et al., 2017; Reinhart & Nguyen, 2019), as an effect localizer.

3. Experiment 2

3.1. Methods

3.1.1. Participants

Forty-one healthy right-handed adults (age, 25.7 ± 11.2; 26 women, 10 men, 5 non-binary or other gender) participated in this experiment for either course credit or monetary compensation (at a rate of $10/h). The sample size was similar to previous studies which our working memory task (see below) was based on. All participants reported normal or corrected-to-normal vision and no history of psychiatric or neurological disorders. The experiment protocol was approved by the University of Connecticut Institutional Review Board. Participants gave their informed written consent before participating in the studies.

3.1.2. Experiment design

The design of Experiment 2 was similar to that of Experiment 1: The primary change was that we included two additional subtasks: an object change detection subtask and an orientation judgment subtask (replicating the design used by Daume et al. (2017) and Reinhart and Nguyen (2019). These two subtasks are collectively referred to in this paper as the "working memory task" whereas the language task is referred to as the "sentence comprehension task". As noted above, TG-PAC is thought to reflect domain-general representational content (Lisman, 2005). As such, we hypothesized that if TG-PAC underlies the representation of an object evoked through a visual image (as in our working memory task), it might also support the representation of an object evoked through language.

3.1.2.1. Sentence comprehension task. Participants completed the sentence comprehension task first. Due to timing constraints, we sampled 120 minimal pairs of sentences from the previous experiments and counterbalanced them across two lists such that each list contained 60 sentences from each condition (120 in total). To verify the categorical difference between these sentences, we obtained, from a prior norming study, the degree-of-change ratings (1–7 Likert scale) that a separate group of participants had provided for these sentences (40 ratings per sentence). Indeed, an independent *t*-test confirmed substantial change sentences (M = 4.50, SD = 0.89) involved a significantly greater change to the object than minimal change sentences (M = 1.81, SD = 0.56), $t(238) = 27.84$, $p < 0.001$.

Sentences were presented word-by-word with a 600 ms ISI, and on a quarter of trials, were followed by yes/no questions to encourage participant engagement in the task. These questions were designed to test high-level comprehension of the events described in the sentences. Some probed the subjects, verbs, or objects of the sentences (e.g., "will the chef peel a piece of garlic?") while others asked about implied instruments (e.g., "was there a knife involved?"); participants responded by pressing the J and F keys (for yes and no respectively). The aim was to provide a variety of question types such that participants could not answer them by simply paying attention to specific words in each sentence. Trial order was pseudorandomized beforehand and fixed for both lists so that they proceeded in the same order–that is, the first sentence in list one had its minimal pair counterpart as the first sentence in list two. As in Experiment 1, each participant read only one sentence from each minimally-different sentence pair.

3.1.2.2. Working memory task. After completing the sentence comprehension task, participants performed a working memory task which was designed similarly to the ones reported in Daume et al. (2017) and Reinhart and Nguyen (2019). This working memory task consisted of two subtasks: a change detection subtask designed to engage working memory processes, and an orientation judgment subtask which acted as a control (Fig. 2, bottom). Participants were first introduced to the change detection subtask and completed 10 practice trials (with feedback), then did the same for the orientation judgment subtask. They then had the opportunity to clarify any final points with the researcher before commencing the rest of the experiment. Participants completed 10 blocks alternating between the change detection subtask and the orientation judgment subtask, with a short break in the middle. Each block contained 20 trials, resulting in 100 trials total per subtask. At the beginning of each block, participants were shown a prompt about the upcoming task, as well as a brief reminder of the task itself. Trial order for both tasks was pseudorandomized and fixed across participants such that everybody saw the same set of images for the change detection subtask, and a different set of images for the orientation judgment subtask. Since this visual working memory task as a whole was intended as a localizer, keeping trials consistent across participants outweighed the benefits of counterbalancing.

3.1.2.3. Change detection subtask. The change detection subtask was designed to elicit working memory maintenance of a single image. Trials in the change detection subtask started with a fixation dot in the middle of the screen (2000 ms; Fig. 2, bottom), followed by a line drawing of an object (encoding image; 200 ms), then a short delay (3000 ms). Participants were instructed to remember the image during this delay. Following the delay, another image was shown (cued image; 200 ms), and participants had to judge if both the first and second images were identical (J key for yes, F key for no). On half the trials, the cued image matched the encoding image; on the other half, it was slightly different–we used a subset of the stimuli in Daume et al. (2017), who had modified the original stimuli from Snodgrass and Vanderwart (1980) to produce minimally-different, yet perceptually distinguishable minimal pairs of images. Participants received feedback on their accuracy after each response.

3.1.2.4. Orientation judgment subtask. Participants also did an orientation judgment subtask as a control for the change detection subtask. As in the change detection subtask, trials began with a line drawing (200 ms), followed by a delay (3000 ms). However, participants were told they did *not* have to remember the image. Instead, an ellipse flashed briefly (50 ms) after the delay, and participants were asked to judge whether this ellipse was oriented horizontally (J key) or vertically (F key). Half the ellipses were oriented vertically and half were oriented horizontally. Since the change-detection subtask required memory of the initial image while the orientation judgment subtask did not, neural activity during the 3-s delay in the change-detection subtask was presumed to reflect the active maintenance of an image in working memory while controlling for attentional demands.

Following Daume et al. (2017), we dynamically adapted difficulty on the orientation judgment subtask to balance accuracy with the change-detection subtask. At the end of each change-detection block, the cumulative accuracy across all change-detection trials and orientation judgment trials were calculated separately. Based on the difference between these cumulative accuracies, the experiment script adjusted a

single difficulty parameter which varied both the ellipse's height/width ratio and its opacity. If, up until that point, the participant had performed better on the orientation judgment subtask, then the subsequent orientation judgment block was made more challenging. Likewise, if they had done better on the change-detection subtask overall, then the next orientation judgment block was easier. The goal with this balancing was to mitigate the risk that any obtained TG-PAC effect might be attributed to task engagement rather than the working memory processes of interest.

3.1.3. EEG

EEG was recorded using 64-channel gel-based BrainVision ActiCHamp EEG systems at a sampling rate of 500 Hz without online filtering. Electrodes were set up in a standard 64Ch-actiCAP configuration, with the ground electrode at FPz and online reference at Cz. The experiment was conducted in an electrically-shielded, sound-dampened room, and the experiment script was written and presented in Psychopy version 2022.2.4 (Peirce et al., 2019). Participants were instructed to sit centered at a comfortable distance from the computer screen and place their left and right index fingers on the F and J keys respectively. EEG data was preprocessed using the same steps as in Experiment 1, and one participant was excluded for excessive noise in their EEG recording. On average, 92.5 ± 7.7 trials were retained per participant for the change detection subtask and 92.2 ± 8.5 in the orientation judgment subtask. For the sentence comprehension task, there were 55.1 ± 5.4 and 56.5 ± 5.9 trials in the substantial change and minimal change conditions respectively.

3.2. Analysis

Spectral power analysis was computed using 7-cycle Morlet wavelets on the epoched data, across 100 frequency bands geometrically spaced from 3 to 80 Hz for each participant and condition. The time window of analysis differed depending on the task. For the working memory task, epochs were − 0.5 to 3.0 s relative to trial onset; for the sentences, epochs spanned −0.5 to 8.0 s relative to trial onset. Epochs were baselined to the 0.5 s window preceding the onset of the trial. Spectral power was computed at each timepoint, then averaged within consecutive bins of 500 ms to reduce computational complexity. The power difference between conditions in each respective task was then calculated for each participant and subjected to a cluster-based permutation test, as in Experiment 1, along the dimensions of time, frequency, and space. Although we did not predict differences in power in the sentence comprehension task, it is known to affect some measures of PAC (Daume et al., 2017; Dupré la Tour et al., 2017; van Wijk et al., 2015) and was thus relevant to the interpretation of our results.

TG-PAC was calculated in the same manner as in Experiment 1, across a time window of 0.2–3.2 s for the working memory task (both change detection and orientation judgment subtasks) and 1.8–8.0 s (i.e. from the onset of the verb) for the sentence comprehension task. Following Daume et al. (2017) and Reinhart and Nguyen (2019), we characterized our working memory effect as the difference in TG-PAC between the change-detection and orientation judgment subtasks.

To identify a working memory PAC cluster, we first pooled all trials from each condition across subjects and calculated the TG-PAC difference between the change-detection subtask and the orientation judgment subtask for each phase/amplitude frequency pair and channel. We then generated surrogate data by shuffling trials between conditions (1024 shuffles) and recalculating the TG-PAC difference on each shuffled partition. This resulted in a surrogate distribution of 1024 TG-PAC differences. The actual TG-PAC difference scores at each phase/amplitude/channel point were then compared against this surrogate distribution to obtain corresponding *p*- and *t*-values. As in Experiment 1, adjacent points (in phase/amplitude frequency and channel space) falling below a *p*-value of 0.01 were grouped together into clusters. We thus identified clusters for the working memory task by comparing against a surrogate distribution; again, cluster sizes were determined by summing the *t*-values of points within each cluster.

The largest cluster obtained using this method matched the left temporal topography found in Experiment 1 and elsewhere (Daume et al., 2017; Reinhart & Nguyen, 2019), and was subsequently used as a region-of-interest (ROI) for the sentence comprehension task. As the distribution of TG-PAC values within this cluster did not satisfy the assumption of normality based on a Shapiro-Wilk test ($W = 0.79$, $p < 0.001$), we calculated the TG-PAC difference between substantial and minimal change using a Wilcoxon signed-rank test.

In addition to this categorical split, we also ran a continuous analysis. Prior work suggests that the brain is sensitive to the *degree* of change to an object, over and above the substantial vs minimal contrast (Hindy et al., 2012; Solomon et al., 2015). We thus ran a simple linear regression using degree of change ratings (which had been obtained in a prior norming study) to investigate whether TG-PAC similarly reflects this graded quality. One potential concern is that any result obtained this way may not be specific to the frequency/channel triplets (i.e. each conjunction of phase frequency, amplitude frequency, and channel) in our working memory cluster; but instead be due to a *global* increase in TG-PAC for sentences with greater degrees of change. To address this, we compared our data against a surrogate distribution derived from 10,000 random contiguous clusters. For each surrogate, we initialized a random contiguous cluster of the same size as our working memory cluster, applied it to our data as an ROI, and computing a linear regression against degree of change to obtain a surrogate distribution of 10,000 β-values. Our real β-value was then compared against this surrogate distribution.

3.3. Results

3.3.1. Spectral power

Analysis of the difference in spectral power between the change detection subtask and the orientation judgment subtask revealed a significant cluster spanning the delay window (0 – 3000 ms) and alpha to gamma frequencies (8–80 Hz) (Fig. 4; cluster $p < 0.01$). No significant clusters were found in the sentence task, between sentences with substantial change and sentences with minimal change. As such, any differences in PAC for the sentence comprehension task are unlikely to be attributable to differences in spectral power.

3.3.2. Phase-amplitude coupling

Phase-amplitude coupling analysis of the working memory task revealed a cluster of left temporal electrodes including T7, TP7, and C5 (based on the International 10–20 system), spanning 4–7 Hz and 32–50 Hz (Fig. 5A and B). This topography overlapped with that obtained in Experiment 1 (and elsewhere in the literature); all three of these positions were also contained in the cluster in Experiment 1, as confirmed by the electrodes' correspondence to international standard positions per EGI's technical documentation (Luu & Ferree, 2005). Within this cluster, TG-PAC was greater for change detection trials compared to control trials. Using this working memory cluster as an ROI mask, we then analyzed TG-PAC differences in the sentence task. TG-PAC for minimal change sentences was subtracted from TG-PAC for substantial change sentences at each frequency-channel triplet, and the resulting values submitted to a Wilcoxon signed-rank test. This revealed significantly greater TG-PAC within the cluster for substantial change sentences compared to minimal change sentences ($W = 421$, $p < 0.001$).

The results above indicate increased TG-PAC for sentences with "substantial" change compared to "minimal" change to the object. If TG-PAC depends not just on the fact that there is a change of state, but is sensitive to the amount of change that happens in the sentence, then it should covary with the *degree* of change to the object. To analyze this, we ran a linear regression using rated degree of change (obtained in a previous norming study) rather than the a priori defined categories of "substantial" or "minimal" change. A simple linear regression showed

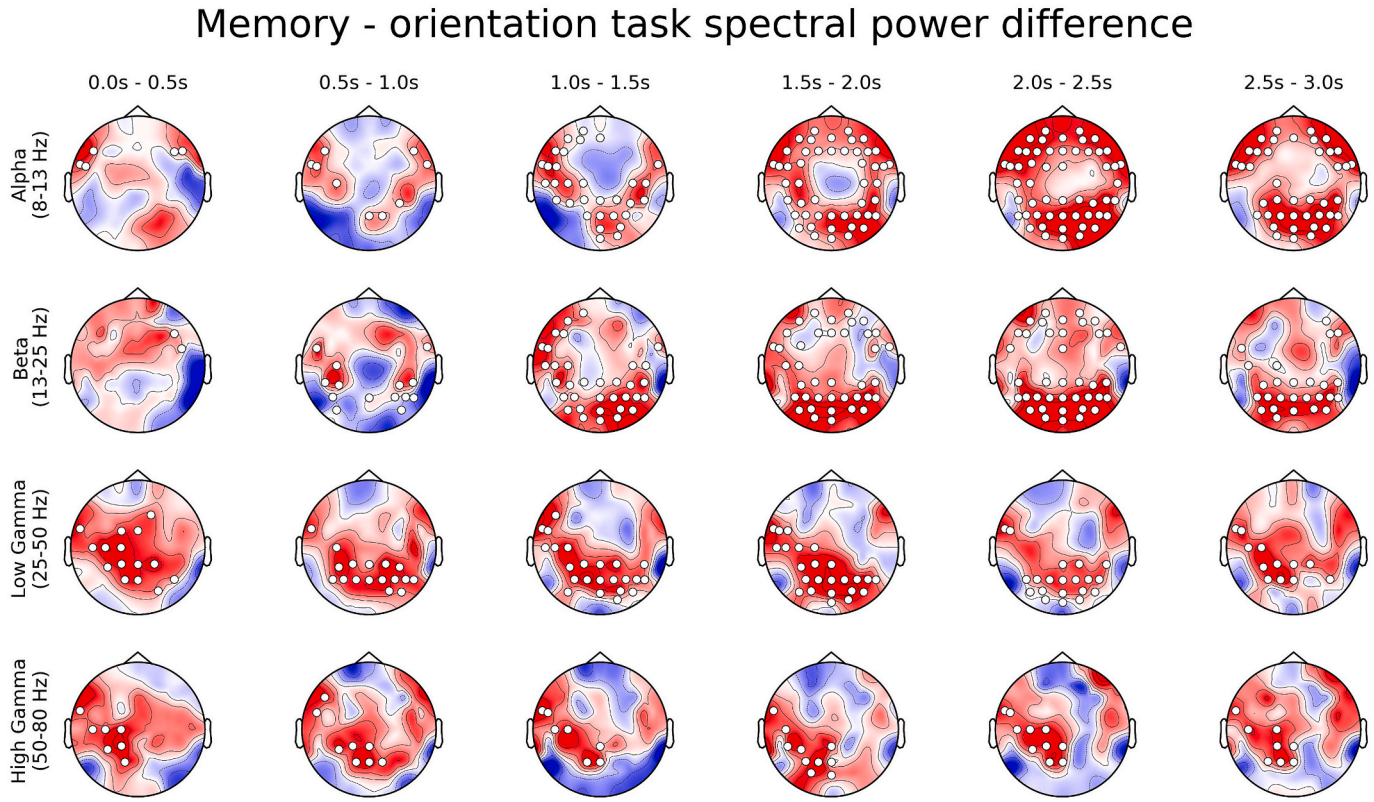


Fig. 4. Spectral power differences in the working memory task, averaged within frequency bands and 500 ms bins within the delay period.

that degree of change significantly predicted average TG-PAC within our ROI (Fig. 5C; $\beta = 0.16$, $p < 0.01$). To test the specificity of this effect, we generated a surrogate distribution of β-values using 10,000 random contiguous ROIs of the same size as the original. Our obtained β-value was statistically significant when compared against this surrogate distribution (Fig. 5D; $p < 0.001$).

One might suggest alternative explanations for the relationship between TG-PAC and degree of change which place less emphasis on working memory (or the maintenance of an object or object-states). For example, perhaps TG-PAC reflects the initial transformation of the object (e.g., the chopping of the onion), scaling with the magnitude of that transformation, and, correspondingly, with the degree of change to the object. If so, we would predict TG-PAC to vary with degree of change in the *first* half of each sentence (e.g., "the chef will chop the onion") – that is, when this initial transformation operation is expected to happen in the mind. To control for this possibility, we re-ran the analysis above on epochs encompassing just the first sentence (t = 0–3.6 s). Within this earlier analysis window, there was no significant relationship between TG-PAC and degree of change ($\beta = -0.01$, $p = 0.81$), ruling out the initial transformation operation as a source of our TG-PAC effect.

4. General discussion

Across two EEG experiments, we present evidence that when comprehending sentences like "the chef will chop the onion, and then he will smell it", multiple object-states are maintained online in the brain via theta-gamma phase-amplitude coupling. In the first experiment, we observed a non-significant TG-PAC cluster in left temporal electrodes when contrasting substantial and minimal change sentences. To increase our sensitivity to detect an effect, we designed a second experiment that included a visual working memory task as a functional localizer. This task yielded a left temporal TG-PAC cluster, which we then used as an ROI for the sentence comprehension task. Within this ROI, we found increased TG-PAC for substantial change compared to minimal change sentences. Furthermore, we found sensitivity to the *amount* of change to the object above and beyond our categorical findings–TG-PAC increased with greater degree of change to the object.[1] Thus, whatever the functional role TG-PAC plays in the representation of multiple object-states bound to the same object, it appears sensitive to the magnitude of change that an object undergoes as a consequence of the event it participates in. We discuss consequences of this sensitivity further below.

4.1.1. Functional role of TG-PAC

Our results show that the multiple object-states in a state-change sentence may indeed be maintained online in the discourse by processes to which TG-PAC is sensitive (although as we alluded to earlier, TG-PAC may *constitute* that maintenance), prior to their retrieval when cued in the sentence (Hindy et al., 2012; Solomon et al., 2015). This raises questions about the functional role of TG-PAC, or about the content that TG-PAC reflects. As outlined earlier, one hypothesis is that TG-PAC is sensitive to or is a carrier of sequential domain-general information (Lisman, 2005). Under this hypothesis, TG-PAC, or what it reflects, underlies the maintenance of a visual object in working memory, as abundantly demonstrated in the visual working memory literature. Applying the same framework to our results suggests it is also the

[1] An alternative analysis would have been to perform the equivalent of a searchlight analysis in fMRI – asking whether there is any cluster in sensor space that shows sensitivity of TG-PAC to degree-of-change. One could then ask whether any such cluster overlapped with the established TG-PAC difference observed in the literature on TG-PAC and working memory. This analysis would be similar to the specificity analysis that compares our degree-of-change result in the working memory cluster against a surrogate distribution of random contiguous ROIs (Figure 5D).

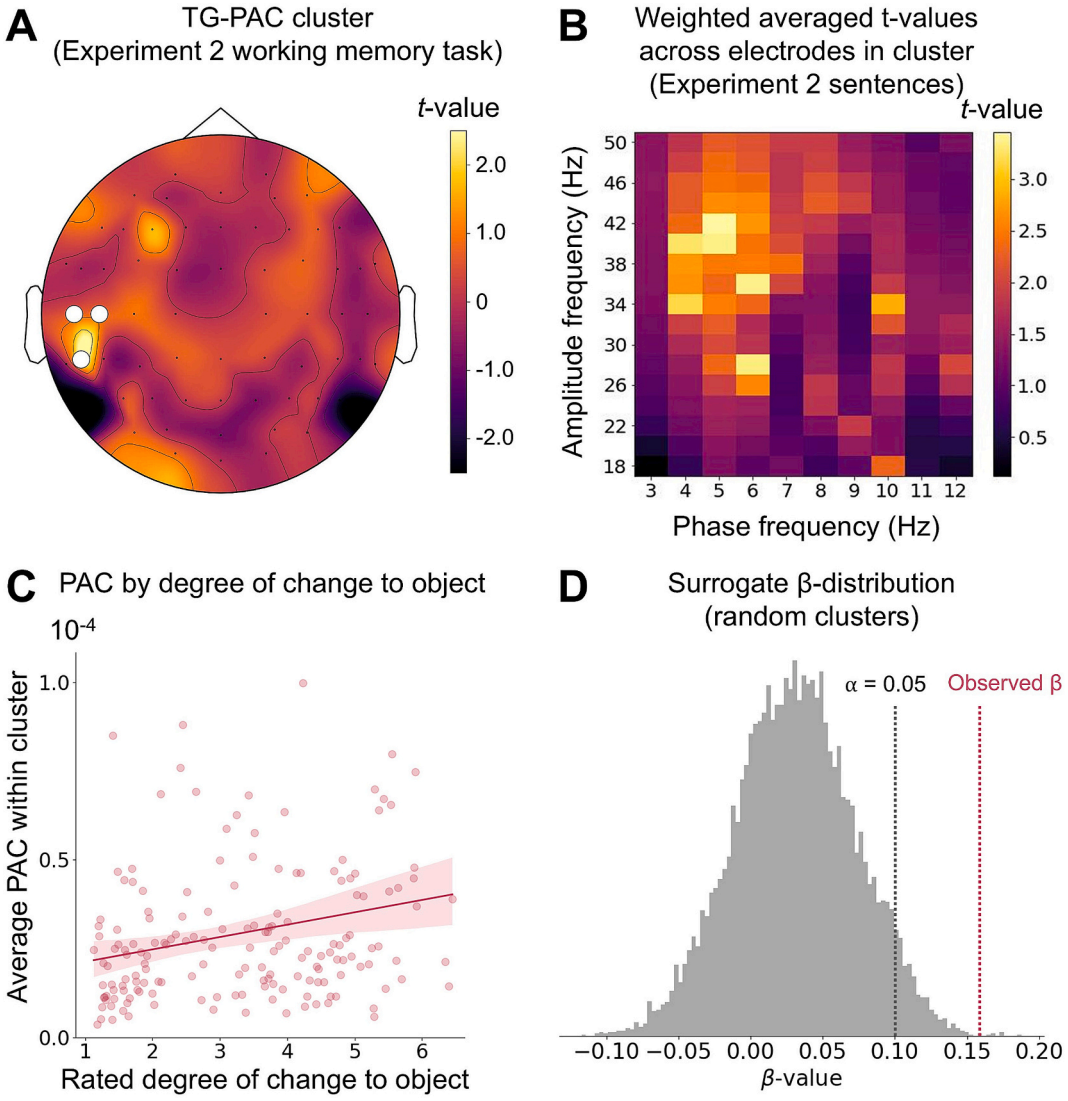


Fig. 5. TG-PAC results for Experiment 2. **A:** Largest cluster of TG-PAC difference for the working memory task (change detection - orientation judgment subtasks). **B:** Comodulogram showing t-values averaged across channels, weighted by the number of cells from each channel within the cluster, for each phase-amplitude frequency pair (sentence comprehension task). **C:** TG-PAC strength increases with rated degree of change to the object. One outlying point (>Mean + 3.5 SD) has been omitted from the graph for clarity. **D:** Linear regression results compared against a surrogate distribution generated using random clusters of the same size.

mechanism by which we represent object-states, bound to the same token but separated through time, that have been instantiated via sentence comprehension. This implicates TG-PAC as reflecting one potential mechanism to address the binding problem in language–the binding of specific features to their corresponding objects (Treisman, 1996; and see Yu & Lau, 2023); Object-state representations (c.f. sets of features) must be bound to the same object token, regardless of whether those representations are instantiated via vision or language, and this binding may therefore be encoded by the same neural processes. While our findings offer preliminary evidence of this possibility, demonstrating its robustness across other paradigms in vision and language remains an important goal for future research (see Limitations section below).

We find that TG-PAC, like the prior fMRI effects obtained by Hindy et al. (2012) and Solomon et al. (2015), is sensitive to degree of change to the object. Thus, the TG-PAC we observed cannot simply have been due to the *cardinality* of object-states in the sentence. Whatever functional role it reflects, it is stronger when the states maintained in working memory are more dissimilar to each other. This raises the question: What is the source of its sensitivity to degree of change? We approach this question by (re)considering the finding discussed earlier that theta oscillations reflect integration of perceptual representations in memory (Clouter et al., 2017) and gamma oscillations reflect the encoding of individual items (Kaiser et al., 2008). If integration of object-state representations into a single object token is harder when those representations are more dissimilar, we should expect TG-PAC, in light of these findings, to be sensitive to (dis)similarity. As to why integration is harder when object states are more dissimilar, we suppose that dissimilar representations of object states require more representational resources (more features distributed further afield in feature space) than more similar representations of object states.

Our finding that TG-PAC can coordinate the encoding of multiple object-states bound to the same object, against the backdrop of literature showing its role in representing multiple distinct objects in sequence (Axmacher et al., 2010; Heusser et al., 2016; Lisman & Jensen, 2013), leads to an apparent conundrum: How does it scale up when there are multiple objects in multiple states? We offer a preliminary hypothesis, but note that this warrants further investigation as, to our knowledge, how the mind/brain represents the *same* object in multiple states across time is unspecified in both Lisman's (2005) theory of TG-PAC and many object-based models of visual working memory (e.g., Luck & Vogel,

1997; Vogel et al., 2001; Zhang & Luck, 2008).

Our proposal stems from considering not just events as sequential ensembles of objects, but objects *themselves* as ensembles of states through time (Altmann & Ekves, 2019). We hypothesize that different neuronal subpopulations may instantiate TG-PAC at different levels of representational hierarchy. In this framework, TG-PAC continues to serve a domain-general role in organizing sequences, but its functional content varies with the level of abstraction. While higher-order TG-PAC ensembles organize objects within a sequence, the neuronal assemblies corresponding to these objects could in turn function as object indices (e.g., Kahneman et al., 1992; Pylyshyn, 1989) which "point" in some way to lower-order ensembles; these lower-level ensembles would reflect the object-states (or features) bound to a single object (Köster et al., 2018). Under this account, the maintenance of individual objects would be functionally dissociable from the maintenance of their trajectories through state space. Indeed, such a view appears consistent with "hybrid" models of visual working memory, which posit partially independent processes for representing objects and their features (e.g., Brady et al., 2011; Cowan et al., 2013; Oberauer & Eichenberger, 2013). How TG-PAC interacts both with the number of object-states *and* the number of individual objects in working memory is thus a potential avenue for future investigation.

What might be the anatomical basis for TG-PAC in the sentence comprehension task? As mentioned earlier, experimental evidence points to TG-PAC in working memory as originating in the hippocampus (e.g., Axmacher et al., 2010; Bragin et al., 1995; Daume et al., 2024). But a few studies, including Daume et al. (2017) and Reinhart and Nguyen (2019), detected the effect in sensor space with a profile similar to ours. If indeed the TG-PAC identified in our experiments is hippocampal in origin, this would implicate the hippocampus as the binding site for these object tokens. Such an explanation ties in with literature implicating the hippocampus in constructing scenes (Barry et al., 2019; Hassabis & Maguire, 2007) and object tokens through relational binding (Eichenbaum et al., 2007; Moscovitch et al., 2016), particularly through language (Duff & Brown-Schmidt, 2012). As such, while we cannot declare the hippocampus to be the origin of our TG-PAC finding in the sentence comprehension task (in the absence of source space measures), it would be consistent with the broader literature.

4.1.2. Theoretical implications

Our findings show a common neural process underlying the maintenance of visually- and linguistically-evoked objects. This builds on theories that language comprehension engages the same psychological processes involved in visual perception (Barsalou, 2003; Barsalou, 2008; Bransford et al., 1972; Johnson-Laird, 1983; Van Dijk & Kintsch, 1983), and adds to the growing literature showing that understanding a state-change sentence activates object representations that preserve aspects of their visual form (Connell, 2007; Hambric et al., 2026; Hindy et al., 2012, 2015; Horchak & Garrido, 2024; Kang et al., 2020; Lee & Kaiser, 2026; Prystauka et al., 2024; Solomon et al., 2015; Stanfield & Zwaan, 2001; Wing & Altmann, 2026; Zwaan et al., 2002). Hindy et al. (2015), in particular, showed that the comprehension of these sentences recruits the neural substrates involved in vision. When participants were asked to imagine objects undergoing change (e.g., "inflate the balloon"), cortical activation patterns in their visual cortex correlated with the degree of change to the object–the greater the change, the more dissimilar the patterns were, suggesting that this state-change was evoked in visual areas. Our findings complement this body of work by suggesting a perceptually-grounded mechanism by which we *maintain* linguistically-evoked object representations as the sentence unfolds.

Combined with prior work (Hindy et al., 2012, 2015; Solomon et al., 2015), our findings suggest a time course from the evocation of object-states in state-change sentences to their retrieval. When we comprehend a sentence like "the chef will chop the onion", we instantiate, minimally, the object-states that reflect the initial and end states; these are bound to the same onion token in the mind (Hindy et al., 2012; Solomon et al., 2015). These representations are maintained online via TG-PAC as the sentence continues with "and then he will smell…", until they are cued for retrieval by the onion. At this point the left vLPFC selects between these object-states (Hindy et al., 2012; Solomon et al., 2015). It remains to be seen if this selection triggers the cessation of TG-PAC, or if the object-states continue to be held in the brain for future use. Such analyses are difficult to implement with current techniques for analyzing phase-amplitude coupling, as they typically require epochs of at least a few seconds (Seymour et al., 2017; Tort et al., 2010). However, novel techniques are emerging (e.g., Weissbart & Martin, 2024) which may be better suited to target these transient changes in PAC strength. Future experiments might thus leverage techniques with greater spatiotemporal resolution to tease apart these effects.

4.1.3. Limitations

There is a strong sense in which our experimental design–using a visual working memory TG-PAC result to localize an effect in the sentence task–was a proof-of-concept, intended to show that the neural signal for visual working memory *can* overlap with those used to represent object-states in language. However, we acknowledge some limitations of this study that warrant further investigation of this phenomenon.

As with most controlled language experiments, it remains to be seen if our findings will scale up to more naturalistic contexts or other sentence types. For example, one could test whether the TG-PAC effects are obtained with sentences in which the *object* varies instead of the verb, while still manipulating the degree of change (e.g., "the girl will stomp on the egg/penny"). Such a finding would rule out TG-PAC as driven by lexical properties of the verb, rather than event-level features as a whole. Indeed, Hindy et al. (2012) investigated these sentences in fMRI and found comparable effects across both sentence types, suggesting that representational conflict was driven by the object-states in question rather than the verbs. To the extent that our findings reflect the same underlying representational requirements, one might expect our TG-PAC result to be replicated with these sentences as well, but that remains an empirical question.

The visual task we used also did not vary the number or *similarity* of object-states, which have been shown to be central components of the difference between substantial and minimal state-change sentences in the brain (Hindy et al., 2012; Solomon et al., 2015). To our knowledge, however, no experiment has shown how TG-PAC interacts with visual object similarity. Future work will therefore examine these interactions using working memory tasks that bear more resemblance to the kinds of representations we expect to arise in events of object state change. We thus see this as a first step in highlighting TG-PAC as a candidate signal for the non-linguistic representations elicited through language.

CRediT authorship contribution statement

Wesley Leong: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Gerry T.M. Altmann:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We would like to thank Zachary Ekves and Yanina Prystauka, who collected the data used in Experiment 1. We would also like to thank the Connecticut Institute for the Brain and Cognitive Sciences for providing

resources for the experiments in this paper.

Funding information

This research was supported by a Jorgensen Fellowship awarded to the first author and a seed grant from the Connecticut Institute for the Brain and Cognitive Sciences.

Data availability

Scripts to run the analyses are available upon request. We do not have IRB approval to share the EEG data.

References

Altmann, G., & Ekves, Z. (2019). Events as intersecting object histories: A new theory of event representation. *Psychological Review, 126*(6), 817–840. https://doi.org/10.1037/rev0000154

Axmacher, N., Henseler, M., Jensen, O., Weinreich, I., Elger, C., & Fell, J. (2010). Cross-frequency coupling supports multi-item working memory in the human hippocampus. *Proceedings of the National Academy of Sciences of the United States of America, 107*, 3228–3233. https://doi.org/10.1073/pnas.0911531107

Bahramisharif, A., Jensen, O., Jacobs, J., & Lisman, J. (2018). Serial representation of items during working memory maintenance at letter-selective cortical sites. *PLoS Biology, 16*(8), Article e2003805. https://doi.org/10.1371/journal.pbio.2003805

Barry, D. N., Barnes, G. R., Clark, I. A., & Maguire, E. A. (2019). The neural dynamics of novel scene imagery. *Journal of Neuroscience, 39*(22), 4375–4386.

Barsalou, L. W. (2003). Situated simulation in the human conceptual system. *Language and Cognitive Processes, 18*(5–6), 513–562. https://doi.org/10.1080/01690960344000026

Barsalou, L. W. (2008). Grounded cognition. *Annual Review of Psychology, 59*(1), 617–645.

Barsalou, L. W., Simmons, W. K., Barbey, A. K., & Wilson, C. D. (2003). Grounding conceptual knowledge in modality-specific systems. *Trends in Cognitive Sciences, 7*, 84–91. https://doi.org/10.1016/S1364-6613(02)00029-3

Berman, J. I., McDaniel, J., Liu, S., Cornew, L., Gaetz, W., Roberts, T. P. L., & Edgar, J. C. (2012). Variable bandwidth filtering for improved sensitivity of cross-frequency coupling metrics. *Brain Connectivity, 2*(3), 155–163. https://doi.org/10.1089/brain.2012.0085

Brady, T. F., Konkle, T., & Alvarez, G. A. (2011). A review of visual memory capacity: Beyond individual items and toward structured representations. *Journal of Vision, 11*(5), 4. https://doi.org/10.1167/11.5.4

Bragin, A., Jando, G., Nadasdy, Z., Hetke, J., Wise, K., & Buzsaki, G. (1995). Gamma (40–100 Hz) oscillation in the hippocampus of the behaving rat. *Journal of Neuroscience, 15*(1), 47–60. https://doi.org/10.1523/JNEUROSCI.15-01-00047.1995

Bransford, J. D., Barclay, J. R., & Franks, J. J. (1972). Sentence memory: A constructive versus interpretive approach. *Cognitive Psychology, 3*(2), 193–209. https://doi.org/10.1016/0010-0285(72)90003-5

Canolty, R. T., Edwards, E., Dalal, S. S., Soltani, M., Nagarajan, S. S., Kirsch, H. E., … Knight, R. T. (2006). High gamma power is phase-locked to Theta oscillations in human neocortex. *Science, 313*(5793), 1626–1628. https://doi.org/10.1126/science.1128115

Chaieb, L., Leszczynski, M., Axmacher, N., Höhne, M., Elger, C. E., & Fell, J. (2015). Theta-gamma phase-phase coupling during working memory maintenance in the human hippocampus. *Cognitive Neuroscience, 6*(4), 149–157. https://doi.org/10.1080/17588928.2015.1058254

Chavez, M., Besserve, M., Adam, C., & Martinerie, J. (2006). Towards a proper estimation of phase synchronization from time series. *Journal of Neuroscience Methods, 154*(1), 149–160. https://doi.org/10.1016/j.jneumeth.2005.12.009

Clouter, A., Shapiro, K. L., & Hanslmayr, S. (2017). Theta phase synchronization is the glue that binds human associative memory. *Current Biology, 27*(20), 3143–3148.e6. https://doi.org/10.1016/j.cub.2017.09.001

Connell, L. (2007). Representing object colour in language comprehension. *Cognition, 102*(3), 476–485. https://doi.org/10.1016/j.cognition.2006.02.009

Cowan, N., Blume, C. L., & Saults, J. S. (2013). Attention to attributes and objects in working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 39*(3), 731. https://doi.org/10.1037/a0029687

Curtis, S., De Wit, B., & Kinoshita, S. (2024). Priming the distractor can eliminate the Stroop interference effect. *Psychonomic Bulletin & Review*, 1–9. https://doi.org/10.3758/s13423-024-02610-4

Daume, J., Gruber, T., Engel, A. K., & Friese, U. (2017). Phase-amplitude coupling and long-range phase synchronization reveal frontotemporal interactions during visual working memory. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience, 37*(2), 313–322. https://doi.org/10.1523/JNEUROSCI.2130-16.2016

Daume, J., Kamiński, J., Schjetnan, A. G. P., Salimpour, Y., Khan, U., Kyzar, M., … Rutishauser, U. (2024). Control of working memory by phase–amplitude coupling of human hippocampal neurons. *Nature*, 1–9. https://doi.org/10.1038/s41586-024-07309-z

Duff, M. C., & Brown-Schmidt, S. (2012). The hippocampus and the flexible use and processing of language. *Frontiers in Human Neuroscience, 6*, 69. https://doi.org/10.3389/fnhum.2012.00069

Dupré la Tour, T., Tallot, L., Grabot, L., Doyère, V., van Wassenhove, V., Grenier, Y., & Gramfort, A. (2017). Non-linear auto-regressive models for cross-frequency coupling in neural time series. *PLoS Computational Biology, 13*(12). https://doi.org/10.1371/journal.pcbi.1005893

Dvorak, D., & Fenton, A. A. (2014). Towards a proper estimation of phase-amplitude coupling in neural oscillations. *Journal of Neuroscience Methods, 225*, 42–56. https://doi.org/10.1016/j.jneumeth.2014.01.002

Eichenbaum, H., Yonelinas, A. P., & Ranganath, C. (2007). The medial temporal lobe and recognition memory. *Annual Review of Neuroscience, 30*, 123–152. https://doi.org/10.1146/annurev.neuro.30.051606.094328

Ekves, Z. (2022). *Bottom-up influences on repeat object reference* [Doctoral Dissertation]. University of Connecticut.

Fell, J., & Axmacher, N. (2011). The role of phase synchronization in memory processes. *Nature Reviews Neuroscience, 12*(2), 105–118. https://doi.org/10.1038/nrn2979

Gramfort, A., Luessi, M., Larson, E., Engemann, D., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., & Hämäläinen, M. (2013). MEG and EEG data analysis with MNE-Python. *Frontiers in Neuroscience, 7*. https://doi.org/10.3389/fnins.2013.00267

Groppe, D. M., Urbach, T. P., & Kutas, M. (2011). Mass univariate analysis of event-related brain potentials/fields I: A critical tutorial review. *Psychophysiology, 48*(12), 1711–1725. https://doi.org/10.1111/j.1469-8986.2011.01273.x

Hambric, C. E., Sides, J., Holmes, K. J., & Kumar, A. A. (2026). Representing object state change during sentence comprehension: Boundary conditions and language-specific constraints. *Journal of Memory and Language, 149*, Article 104764. https://doi.org/10.1016/j.jml.2026.104764

Hassabis, D., & Maguire, E. A. (2007). Deconstructing episodic memory with construction. *Trends in Cognitive Sciences, 11*(7), 299–306.

Heusser, A. C., Poeppel, D., Ezzyat, Y., & Davachi, L. (2016). Episodic sequence memory is supported by a theta–gamma phase code. *Nature Neuroscience, 19*(10), Article 10. https://doi.org/10.1038/nn.4374

Hindy, N. C., Altmann, G. T. M., Kalenik, E., & Thompson-Schill, S. L. (2012). The effect of object state-changes on event processing: Do objects compete with themselves? *Journal of Neuroscience, 32*(17), 5795–5803. https://doi.org/10.1523/JNEUROSCI.6294-11.2012

Hindy, N. C., Solomon, S. H., Altmann, G. T. M., & Thompson-Schill, S. L. (2015). A cortical network for the encoding of object change. *Cerebral Cortex, 25*(4), 884–894. https://doi.org/10.1093/cercor/bht275

Holz, E. M., Glennon, M., Prendergast, K., & Sauseng, P. (2010). Theta-gamma phase synchronization during memory matching in visual working memory. *NeuroImage, 52*(1), 326–335. https://doi.org/10.1016/j.neuroimage.2010.04.003

Hopper, P. J. (1979). Aspect and foregrounding in discourse. In *, 12. Syntax and semantics*.

Horchak, O. V., & Garrido, M. V. (2024). Language comprehenders are sensitive to multiple states of semantically similar objects. *Journal of Memory and Language, 135*, Article 104478. https://doi.org/10.1016/j.jml.2023.104478

Hyafil, A. (2015). Misidentifications of specific forms of cross-frequency coupling: Three warnings. *Frontiers in Neuroscience, 9*. https://doi.org/10.3389/fnins.2015.00370

Jensen, O., & Lisman, J. E. (2005). Hippocampal sequence-encoding driven by a cortical multi-item working memory buffer. *Trends in Neurosciences, 28*(2), 67–72. https://doi.org/10.1016/j.tins.2004.12.001

Johnson-Laird, P.-N. (1983). *Mental models: Towards a cognitive science of language, inference, and consciousness*. Harvard University Press.

Kahneman, D., Treisman, A., & Gibbs, B. J. (1992). The reviewing of object files: Object-specific integration of information. *Cognitive Psychology, 24*(2), 175–219.

Kaiser, J., Heidegger, T., Wibral, M., Altmann, C. F., & Lutzenberger, W. (2008). Distinct gamma-band components reflect the short-term memory maintenance of different sound lateralization angles. *Cerebral Cortex, 18*(10), 2286–2295. https://doi.org/10.1093/cercor/bhm251

Kang, X., Joergensen, G. H., & Altmann, G. T. (2020). The activation of object-state representations during online language comprehension. *Acta Psychologica, 210*, Article 103162. https://doi.org/10.1016/j.actpsy.2020.103162

Köster, M., Finger, H., Graetz, S., Kater, M., & Gruber, T. (2018). Theta-gamma coupling binds visual perceptual features in an associative memory task. *Scientific Reports, 8*(1), 17688. https://doi.org/10.1038/s41598-018-35812-7

Köster, M., Martens, U., & Gruber, T. (2019). Memory entrainment by visually evoked theta-gamma coupling. *NeuroImage, 188*, 181–187. https://doi.org/10.1016/j.neuroimage.2018.12.002

Larson, E., Gramfort, A., Engemann, D. A., Leppakangas, J., Brodbeck, C., Jas, M., … luzpaz. (2024). *MNE-Python (version v1.7.0)* [Computer software]. Zenodo. https://doi.org/10.5281/zenodo.10999175.

Lee, S. H., & Kaiser, E. (2026). Event knowledge modulates real-time mental representations of object state-change. *Cognitive Science, 50*(1), Article e70165. https://doi.org/10.1111/cogs.70165

Lee, S.-H., Kravitz, D. J., & Baker, C. I. (2012). Disentangling visual imagery and perception of real-world objects. *Neuroimage, 59*(4), 4064–4073. https://doi.org/10.1016/j.neuroimage.2011.10.055

Lisman, J. (2005). The theta/gamma discrete phase code occuring during the hippocampal phase precession may be a more general brain coding scheme. *Hippocampus, 15*(7), 913–922. https://doi.org/10.1002/hipo.20121

Lisman, J., & Buzsáki, G. (2008). A neural coding scheme formed by the combined function of gamma and Theta oscillations. *Schizophrenia Bulletin, 34*(5), 974–980. https://doi.org/10.1093/schbul/sbn060

Lisman, J. E., & Idiart, M. A. (1995). Storage of 7±2 short-term memories in oscillatory subcycles. *Science, 267*(5203), 1512–1515.

Lisman, J. E., & Jensen, O. (2013). The theta-gamma neural code. *Neuron, 77*(6), 1002–1016. https://doi.org/10.1016/j.neuron.2013.03.007

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature, 390*(6657), 279–281. https://doi.org/10.1038/36846

Luu, P., & Ferree, T. (2005). *Determination of the geodesic sensor nets' average electrode positions and their 10 – 10 international equivalents*. Technical Note.

Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG- and MEG-data. *Journal of Neuroscience Methods, 164*(1), 177–190. https://doi.org/10.1016/j.jneumeth.2007.03.024

Moscovitch, M., Cabeza, R., Winocur, G., & Nadel, L. (2016). Episodic memory and beyond: The hippocampus and neocortex in transformation. *Annual Review of Psychology, 67*(1), 105–134.

Oberauer, K., & Eichenberger, S. (2013). Visual working memory declines when more features must be remembered for each object. *Memory & Cognition, 41*(8), 1212–1227. https://doi.org/10.3758/s13421-013-0333-6

Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo, H., … Lindeløv, J. K. (2019). PsychoPy2: Experiments in behavior made easy. *Behavior Research Methods, 51*(1), 195–203. https://doi.org/10.3758/s13428-018-01193-y

Prystauka, Y. (2018). *Comprehending events on the fly: Inhibition and selection during sentence processing* [Master's Thesis]. University of Connecticut.

Prystauka, Y., Wing, E., & Altmann, G. (2024). Investigating the interplay between morphosyntax and event comprehension from the perspective of intersecting object histories. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 50*(6), 985. https://doi.org/10.1037/xlm0001307

Pylyshyn, Z. (1989). The role of location indexes in spatial perception: A sketch of the FINST spatial-index model. *Cognition, 32*(1), 65–97. https://doi.org/10.1016/0010-0277(89)90014-0

Rajji, T. K., Zomorrodi, R., Barr, M. S., Blumberger, D. M., Mulsant, B. H., & Daskalakis, Z. J. (2017). Ordering information in working memory and modulation of gamma by theta oscillations in humans. *Cerebral Cortex, 27*(2), 1482–1490. https://doi.org/10.1093/cercor/bhv326

Reinhart, R. M. G., & Nguyen, J. A. (2019). Working memory revived in older adults by synchronizing rhythmic brain circuits. *Nature Neuroscience, 22*(5), 820–827. https://doi.org/10.1038/s41593-019-0371-x

Roux, F., & Uhlhaas, P. J. (2014). Working memory and neural oscillations: Alpha–gamma versus theta–gamma codes for distinct WM information? *Trends in Cognitive Sciences, 18*(1), 16–25.

Roux, F., Wibral, M., Mohr, H. M., Singer, W., & Uhlhaas, P. J. (2012). Gamma-band activity in human prefrontal cortex codes for the number of relevant items maintained in working memory. *Journal of Neuroscience, 32*(36), 12411–12420.

Rutishauser, U., Ross, I. B., Mamelak, A. N., & Schuman, E. M. (2010). Human memory strength is predicted by theta-frequency phase-locking of single neurons. *Nature, 464*(7290), 903–907. https://doi.org/10.1038/nature08860

Sauseng, P., Klimesch, W., Heise, K. F., Gruber, W. R., Holz, E., Karim, A. A., … Hummel, F. C. (2009). Brain oscillatory substrates of visual short-term memory capacity. *Current Biology, 19*(21), 1846–1852. https://doi.org/10.1016/j.cub.2009.08.062

Seymour, R. A., Rippon, G., & Kessler, K. (2017). The detection of phase amplitude coupling during sensory processing. *Frontiers in Neuroscience, 11*, 487.

Snodgrass, J. G., & Vanderwart, M. (1980). A standardized set of 260 pictures: Norms for name agreement, image agreement, familiarity, and visual complexity. *Journal of Experimental Psychology: Human Learning and Memory, 6*(2), 174.

Solomon, S. H., Hindy, N. C., Altmann, G. T. M., & Thompson-Schill, S. L. (2015). Competition between mutually exclusive object states in event comprehension. *Journal of Cognitive Neuroscience, 27*(12), 2324–2338. https://doi.org/10.1162/jocn_a_00866

Stanfield, R. A., & Zwaan, R. A. (2001). The effect of implied orientation derived from verbal context on picture recognition. *Psychological Science, 12*(2), 153–156. https://doi.org/10.1111/1467-9280.00326

Tamura, M., Spellman, T. J., Rosen, A. M., Gogos, J. A., & Gordon, J. A. (2017). Hippocampal-prefrontal theta-gamma coupling during performance of a spatial working memory task. *Nature Communications, 8*(1), 2182. https://doi.org/10.1038/s41467-017-02108-9

Tort, A. B. L., Komorowski, R., Eichenbaum, H., & Kopell, N. (2010). Measuring phase-amplitude coupling between neuronal oscillations of different frequencies. *Journal of Neurophysiology, 104*(2), 1195–1210. https://doi.org/10.1152/jn.00106.2010

Treisman, A. (1996). The binding problem. *Current Opinion in Neurobiology, 6*(2), 171–178.

Van Dijk, T. A., & Kintsch, W. (1983). *Strategies of discourse comprehension*.

Vogel, E. K., Woodman, G. F., & Luck, S. J. (2001). Storage of features, conjunctions, and objects in visual working memory. *Journal of Experimental Psychology: Human Perception and Performance, 27*(1), 92. https://doi.org/10.1037/0096-1523.27.1.92

Weissbart, H., & Martin, A. E. (2024). The structure and statistics of language jointly shape cross-frequency neural dynamics during spoken language comprehension. *Nature Communications, 15*(1), 8850. https://doi.org/10.1038/s41467-024-53128-1

van Wijk, B. C. M., Jha, A., Penny, W., & Litvak, V. (2015). Parametric estimation of cross-frequency coupling. *Journal of Neuroscience Methods, 243*, 94–102. https://doi.org/10.1016/j.jneumeth.2015.01.032

Wing, E., & Altmann, G. T. (2026). Intermediary object states are activated by sentences describing completed events. *Cognitive Science, 50*(6), Article e70237.

Yu, X., & Lau, E. (2023). The Binding Problem 2.0: Beyond perceptual features. *Cognitive Science, 47*(2), Article e13244. https://doi.org/10.1111/cogs.13244

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature, 453*(7192), 233–235. https://doi.org/10.1038/nature06860

Zwaan, R. A., Stanfield, R. A., & Yaxley, R. H. (2002). Language comprehenders mentally represent the shapes of objects. *Psychological Science, 13*(2), 168–171. https://doi.org/10.1111/1467-9280.00430