Disentangling Semantic Composition and Semantic Association in the Left Temporal Lobe

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Abstract
Although composing two words into a complex representation is conceptually different from forming associations between a pair of words, the brain regions supporting semantic composition have also been implicated for associative encoding. Prior work has never directly compared the neural substrates of composition and association. Here, we adopted a two-word magnetoencephalography (MEG) paradigm which varies compositionality ("French/Korean cheese" vs. "France/Korea cheese") and strength of association ("France/French cheese" vs. "Korea/Korean cheese") between the words. We applied both univariate regression analyses and multivariate pattern classification to the source-localized MEG data in a bilateral language network. We show that the left anterior and middle temporal lobe are distinctly modulated by semantic composition and semantic association. Pattern-based directed connectivity analysis further revealed a continuous information flow from the anterior to the middle temporal region. These findings shed light into a functional dissociation within the left temporal lobe for compositional and distributional semantic processing.

Introduction
When we hear a pair of words such as "coffee" and "cake", we could form a complex meaning of a coffee-flavored cake, or recall an experience where coffee and cake occurred together. These two processes, though conceptually different, have been localized to similar brain regions in the left temporal lobe. For example, a minimal adjective-noun phrase such as "red boat" elicits increased activity in the left anterior temporal lobe (LATL) compared to non-compositional word lists such as "cup, boat" [1,2], and a similar effect has been observed for a language with the reverse word order[3] and for American Sign Language[4], suggesting a role of the LATL in conceptual combination[5]. However, the LATL is also activated when forming arbitrary associations between pairs of words such as "ring" and "cheese"[6], and shows greater oscillatory responses for word pairs with stronger associations[7,8]. Additionally, a temporary virtual lesion induced by repetitive transcranial magnetic stimulation (rTMS) over the LATL significantly slows synonym judgment times[9], mirroring a core feature of semantic dementia (SD) patients with a focal atrophy of the ATL[10-12]. The LATL is also engaged in human face-name[13] and face-location[14] associations, and single neuron recordings in the ATL of macaque monkey's brain suggested that a group of pair-encoding neurons responded only to associated pairs of abstract shapes during the training phase[15,16].

The key challenge to disentangle the neural substrates for semantic composition and semantic association is to orthogonalize the two processes in an experimental design. Prior work has never directly compared the effects of semantic composition and semantic association, and studies on semantic composition using the canonical two-word paradigm are usually confounded with the association factor such that the compositional phrases are also more semantically related than the non-compositional lists. Here we adopted the same two-word paradigm but crossed compositionality and strength of association between the two words using the adjectival and noun forms of a country word and our world knowledge of food. "France cheese" and "French cheese", for example, are highly-associated country-food pairs compared to "Korea cheese" and "Korean cheese". But both "French cheese" and "Korean cheese" are combinatory adjective-noun phrases whereas "France cheese" and "Korea cheese" are merely word lists. This 2 x 2 design enabled us to separate the effects of association and composition during two-word comprehension.

Based on distributional semantic models, we quantified the strength of association between the country word and the food word using the cosine distance of their word embeddings[17] (Fig.

1b). We collected 42 native English speakers' MEG data while they viewed the words one by one on a screen. Highly time-resolved MEG data allow us to characterize the temporal dynamics of semantic association and semantic composition in addition to their spatial locations. Our relatively large sample size also provides more statistical power compared to many prior neuroimaging studies. We coded association and composition as binary variables and applied a mass univariate regression analysis to source-localized MEG data. We restricted the regression analysis to a mask including the left angular gyrus (AG), the left ventromedial prefrontal cortex (vmPFC), the left middle temporal gyrus (LMTG), the left inferior frontal gyrus (LIFG), and the left medial temporal lobe. The left AG and vmPFC have also been implicated in previous literature on conceptual combination[1,18], and the LIFG and the LMTG have been suggested to underlie syntactic combination[19-23]. The medial temporal lobe, on the other hand, has been held critical for associative memory in addition to the anterior temporal lobe[24-29]. As a control, we also included these regions in the right hemisphere. We then performed a multivariate pattern classification analysis within the significant clusters identified by the regression analysis. To further understand the information flow between the active brain regions, we conducted a directed connectivity analysis[21,30,31] using the representational dissimilarity matrices (RDMs) of the MEG data within the functional regions of interest (fROIs).

With this combination of methods, we show that the LATL is most sensitive to the contrast between high and low associative compositional phrases, while the LMTG is mainly driven by the distinction between low-associative compositional phrases and low-associative lists. Directed connectivity analyses suggest a continuous information flow from the LATL to the LMTG. Taken together, our results provide novel evidence that the LATL and the LMTL are distinctly modulated by semantic composition and semantic association. We postulate a functional dissociation within the left temporal lobe for compositional and distributional semantic processing.

Results

Behavioral results. 42 native English speakers (24 female, age 22.3 ± 6.3 years) participated in a picture-matching task while lying supine in a dimly lit, magnetically shielded room. The stimuli comprised of a country adjective/noun and a food noun, with strength of association (Low, High) and compositionality (Comp, List) as factors (Fig. 1a). We quantified the strength of association between the country and food word using the cosine similarity score between the GloVe embeddings[17] of the two words: High associative phrases (e.g., "French/France cheese") have a cosine similarity greater than 0.3 and low associative pairs (e.g., "Korean/Korea cheese") have a cosine similarity lower than 0.15. Note that, although the noun-noun lists (e.g., "France cheese") were not syntactically composable, participants may still attempt conceptual composition during the task. To ensure that the list conditions were indeed non-compositional as intended, we included a single-word control condition. The single-word condition consisted of either a "xxxxx" or a length-matched consonant string (e.g., "xjtgbv") and the critical noun word (i.e., "cheese"). Half of the participants (n=21) saw the "xxxxx" while the other half saw the consonant strings; an ancillary aim of our study was to examine the impact of these two different types of visual baselines but they patterned the same as regards our main manipulation (see Fig. 1a and Supplementary Table 1). During the task, participants saw a country word/nonword and a food noun followed by a picture, and indicated whether it matched the preceding words. For the two-word conditions, the target picture shows a food item with a country flag, and both the country and the food words were required to match; for the one-word condition, the picture contains only a food item (Fig. 1a).

Overall, participants achieved a high accuracy of 90.9% (SD=28.2%) with a mean reaction time (RT) of 1.07 s (SD=0.77 s). We then applied a mixed-effects regression analysis to both accuracy and reaction time with fixed effects for association and composition (with the interaction term), and a random intercept for subjects. To control for the word frequency effect, we also included the log frequency of the first and second word as fixed effects (see "Behavioral data analysis" in Methods for details). As expected, we observed a highly significant word frequency effect on both accuracy and RTs, such that more frequent first word reduced reaction time ($t=-4.68$, $p\sim=0$), and more frequent second word both increased accuracy ($t=3.83$, $p\sim=0$) and reduced reaction time ($t=-6.55$, $p\sim=0$). This typical slowdown in responses for less frequent words indicates that the stimuli are being perceived as intended (Fig. 2b). We also found a significant effect of association for both accuracy and reaction time, where higher association between the two words increased accuracy ($t=1.97$, $p=0.049$) and reduced reaction time ($t=-2.16$, $p=0.03$). However, when controlled for word frequency, the faciliatory effect of composition on accuracy was not significant for either accuracy or reaction time (Fig. 2a).

Spatiotemporal clusters for association and composition. While participants performed the picture-matching task, we collected MEG data using a whole-head 208 channel (7 of the participants' data were collected using a 156 channel MEG, see "Experiment and subject details" in Methods) axial gradiometer system (Kanazawa Institute of Technology, Kanazawa, Japan), at a sampling rate of 1000 Hz with an online 0.1 Hz high-pass filter and a 200 Hz low-pass filter. Cortically constrained estimates of source-level activity were computed from each participant's single-trial responses using dynamical statistical parameter mapping (dSPM)[32]. We conducted a two-stage multiple regression with single-trial source estimates as dependent variables, and compositionality, strength of association and their interaction as predictors (Fig. 3a). The one-word trials were excluded from the regression analysis. Given the significant effects of word frequency on the behavioral results, we also included frequency of the first and second word as control variables. The regression analysis was applied independently to each source within a bilateral mask at each millisecond from 100 millisecond before the onset of the first word to 1200 millisecond post-stimulus onset for each subject. The mask covered regions that have been consistently reported in studies on linguistic combination and associative encoding (see the light pink region in Fig. 4a and 4e). Our analysis searched for significant spatiotemporal clusters within the broadly defined mask instead of simply the LATL in order to maintain maximal ability to identify potentially distinct localizations for association and composition.

Significant clusters for each variable based on adjacent β coefficients over space and time were identified by a cluster-based spatiotemporal permutation test[33] with 10,000 permutations. In all analyses, we used a cluster forming threshold of $p <= 0.05$ with a minimum of 10 neighboring sources and 10 consecutive milliseconds. We identified one significant cluster of 302 sources for the interaction effect between association and composition from 544 to 846 ms ($p=0.019$), which is 54 ms before the onset of the second word till 246 ms afterwards. The cluster covered regions including the anterior temporal lobe, the anterior parts of the inferior, middle and superior temporal gyrus, and the dorsal part of the entorhinal cortex (Fig. 4a) The direction of the interaction is positive, which means that high-association compositional phrases elicited higher activity compared to other conditions (Fig. 4b). The mean fitted activation for the four conditions showed two peaks of opposite polarity within this cluster: For the compositional phrases, high-association was correlated with higher positive activity at the first positive activation period from 544-750 ms, and lower negative activity at the second negative activation period from 750-846 ms. For the non-

compositional list conditions, however, high-association was correlated with less positive activity than low-association at the first positive activation period, and high-association was correlated with increased negative activity than low-association at the second negative activation period (Fig. 4c,d). The peak activity of this interaction effect was localized to the left anterior temporal lobe (MNI coordinates: [-54,5,-11]) at around 680 ms, which is 80 ms after the onset of the second word.

The effect of composition was associated with one significant cluster of 412 sources from 675 to 1050 ms (p=0.032) after the onset of the first word (i.e., 75-450ms after the onset of the second word). The cluster covered regions including the middle posterior parts of the inferior, middle and superior temporal gyrus, and the dorsal part of the entorhinal cortex (Fig. 4e). The sign of the β coefficient is negative, such that compositional phrase induced more negative activity (Fig. 4f). Again, the significant cluster included one positive and one negative activation period. At the first positive period at around 675-750 ms, there is increased positive activity for the list conditions; at the second negative activation period, there is increased negative activity for the composition conditions (Fig. 4h). However, as shown in Fig. 4g, this effect of composition seems to be mainly driven by the difference between composition and lists within the low-associative level. The peak activity of this effect was localized to the left middle temporal gyrus (MNI coordinates: [-49,-11,-19]) at around 815 ms, which is 215 ms after the onset of the noun word, consistent with the typical time window for semantic composition[5].

We also observed a large significant cluster of 498 sources for lexical frequency at the second word in a region spanning left medial-posterior temporal cortex from 820-1200 ms (p=0.038), that is, 220-600 ms after the onset of the second word. Here, higher word frequency decreased activation, consistent with most findings on the effect of frequency[34,35]. The peak activity is located at the inferior middle temporal gyrus (MNI coordinates: [-57,-33,-16]) at around 926 ms. The word frequency effects were regressed out in our calculation of the adjusted fitted activation as shown in Fig. 4d,h. In contrast to word two frequency, word one frequency was not correlated with any significant cluster within the left language mask. No significant cluster was found for any of the effects in the right hemisphere within the mask, suggesting a highly left-lateralized neural activity for association and composition.

To confirm that the list conditions were indeed perceived as non-compositional as the single-word trials, we further conducted post-hoc pair-wise t-tests within the LATL and the LMTL clusters to test this. We expected that the activation timecourse of the list conditions pattern with that of the single-word conditions and this prediction was borne out: No significant temporal clusters were observed for the contrast between the two list conditions and the single word condition in either fROI (see Supplementary Figure 1).

Multivariate pattern classification within the active brain regions. To investigate more fine-grained encodings of the four conditions in the left anterior and middle temporal lobe, we conducted a multivariate pattern classification analysis within the two significant clusters identified by the univariate multiple regression analysis (Fig. 3b). We selected the most responsive sources in the two fROIs at a threshold of $|t| > 1$. This resulted in an LATL fROI with 161 sources, and an LMTL fROI with 108 sources. Under the assumption that patterns of brain activation contain information that distinguishes between the experimental conditions, we applied classification to 4 pairwise combinations of our 4 conditions: high-associative phrases vs high-associative lists, low-associative phrases vs low-associative lists, high-associative phrases vs low-associative phrases, and low-associative phrases vs low-associative lists. The high-associative

phrases vs high-associative lists classification and the low-associative phrases vs low-associative lists classification compares composition across the association levels, and the high-associative phrases vs low-associative phrases classification and the low-associative phrases vs low-associative lists classification compares association across the composition levels.

We trained 4 linear Support Vector Machine (SVM) classifiers with a leave-one-stimulus-pair-out cross-validation procedure. The SVM is a widely used classification method due to its favorable characteristics of high accuracy, ability to deal with high-dimensional data and versatility in modeling diverse sources of data[36]. We chose the linear SVM classifier as it has been shown to perform the best on both MEG[37] and fMRI data[38]. The 4 classifiers were applied separately to all timepoints, and the classification accuracy was estimated by averaging across the 100 cross-validation folds. The same procedure was carried out for each subject, and the classification accuracies for all subjects at each timepoint minus the chance level of 50% were submitted to a cluster-based one-sample t-test with 10,000 permutations within a test window between 600-1200 ms (See "Multivariate pattern classification" in Methods for details).

The classification results are shown in Fig. 5. In the LATL functional ROI, classification accuracy for high-associative composition vs. low-associative composition was significantly higher than chance from 830-935 ms (p=0.019). A cluster for the low-associative composition vs. low-associative lists classifier was identified from 895-950 ms, but it did not survive the permutation significance test (p=0.12). Decoding performance for other classifiers was not significantly higher than chance. Compared with the multiple regression results, we observed the same distinction between high-associative and low-associative compositional phrases. However, high-associative and low-associative lists cannot be successfully decoded from each other, although their averaged activation differ. This suggests a smaller effect size for the distinction between the list conditions in the LATL.

In the LMTL functional ROI, the classifier for the low-associative composition vs. low-associative lists was significant at around 850-935 ms (p=0.035). Other classifiers did not perform significantly better than chance. This is consistent with the pattern observed in the regression results, where the effect of composition seems to be mainly driven by the distinction between composition and list at the low-associative level.

Information flow between the active brain regions. So far we have demarcated the LATL and the LMTL for high- and low-associative compositional phrases, respectively. However, in the temporal dimension, the time windows for the two effects are roughly the same from both the regression and the classification analyses. To further understand how LATL and LMTL exchange information during the two-word comprehension process, we conducted a directed connectivity analysis to estimate the temporal pattern of information flow between the two regions. The analysis is a pattern-based Granger causality analysis using the representational dissimilarity matrices (RDMs) of the source estimates of the 4 conditions from the LATL and the LMTL fROIs. The logic of Granger causality[39] is that time series A "Granger causes" time series B if A contains information that helps predict the future of B better than information in the past of B alone. Here we performed a multivariate pattern-based connectivity analysis which has been applied previously to estimate information flows between brain regions on both visual[30,31] and language processing[21].

We quantified directed connectivity from LATL to LMTL using the partial correlation between the activity of LATL at a previous timepoint and the current activity of LMTL, partialling out the previous activity of LMTL itself. Activities of LATL and LMTL are captured by their data

RDMs, which are the correlation distance (1-Pearson's r) between all combinations of conditions (Fig. 3c). These RDMs indicate the degree to which different levels of associative strength and compositionality evoke similar or distinct response patterns in the neural population. To avoid bias due to the choice of directionality and any specific previous time point, we computed the bidirectional information flow between LATL to LMTL at each timepoint with a time interval of 5 ms before the current timepoint up till 600 ms (5, 10, 15, …600 ms; see "Directed connectivity analysis" in Methods for details). The extended time dimension allows us to determine the extent to which the current activity in the target region is correlated with the source region's activity at each time point within the previous 600 ms.

Overall, mean partial correlations between the previous activity of LATL and the current activity of LMTL (r=0.059) was higher than the mean partial correlations between the previous activity of LMTL and the current activity of LATL (r=0.04). Comparison between the connectivity measures of the two directions revealed significant partial correlations from LATL to LMTL at around 0-300 ms after the onset of the second word. The significant time interval before the current timepoint ranged from almost all the time intervals between 5 to 600 ms (Fig. 6a). No significant partial correlations from LMTL to LATL was found by the contrast measure (Fig. 6b). This suggests that information about associative strength and compositionality of the two words generated in the LATL within the previous 600 ms is continuously delivered to the adjacent LMTL from the onset of the second word to 300 ms post-stimulus onset.

Although the LATL and LMTL functional ROIs in our directed connectivity analysis are selected based on the regression results, this method is still largely data-driven as the connectivity strength is quantified by the partial correlations between the data RDMs. To investigate whether the connectivity results were specific to semantic association and composition or simply reflect intrinsic interactions between two adjacent regions in general, we conducted a supplementary control analysis with the corresponding brain regions in the right hemisphere. Since the RATL and RMTL were not significant to either association or composition effect in the regression analysis, the patterning of data RDMs in the two regions should bear no relation to our stimulus manipulation. Therefore, we expect different connectivity profiles between the two regions in the right hemisphere.

The results supported our prediction: although we did find directed connectivity from RATL to RMTL, the temporal dynamics of the information flow were quite different from that between the LATL and the LMTL. Supplementary Figure 1a showed the contrast between the directed connectivity measures from RATL to RMTL and from RMTL to RATL. There are significant partial correlations from RATL to RMTL from around 150 to 250 ms after the onset of the second word, with a delay of 300-450 ms. No significant partial correlations were found from RMTL to RATL by the contrast measure (Supplementary Figure 1b). Compared to the RATL and RMTL connectivity effect, the information flow from LATL to LMTL is more sustained with a much longer delay window. These additional effects cannot be solely attributed to intrinsic connectivity between adjacent brain regions.

Discussion

Prior work has identified similar brain regions for both semantic composition and associative encoding. This raises the question of whether semantic composition and semantic association can be isolated at the neural level. In theory, semantic compositionality allows human language to express an infinite number of complex expressions from their constituent meanings[40]. This productive combinatory process is not dependent on the semantic relatedness of the constituent

meanings. It engages even for totally novel combinations, such as "green idea". In practice, however, words that occur together are usually semantically related. As stated in distributional semantics, "a word is characterized by the company it keeps"[41], thus a common complex expression like "green grass" involves both combinatory and associative processes.

By orthogonalizing these two factors in the experimental design, we show distinct profiles in the LATL and the LMTL: In the LATL, we observed higher activation for high-associative compositional phrases such as "French cheese" than for low-associative compositional phrases such as "Korean cheese". Multivariate pattern classification also shows distinctive activity patterns between the two conditions. These results suggest that the LATL is most sensitive to commonly encountered complex expressions in everyday life such as "green grass". In the LMTL, the regression analysis and the multivariate pattern classification results indicated that this region is mainly sensitive to the distinction between the composition and list conditions at the low-association level, i.e., the distinction between "Korean cheese" and "Korea cheese". In other words, the LMTL responds more strongly to newly encountered compositional phrases such as "green idea".

We set out to disentangle association and composition in the LATL and we replicated previous findings that the LATL is essential for both factors. In particular, we provide novel evidence that the LATL responded most strongly when the association and composition factors are combined. In addition to the LATL results, we also found an LMTL activity to low-associative compositional phrases. Compared with high-associative compositional phrases, low-associative compositional phrases form a newly-encountered meaning, hence likely involve more syntactic processing for a successful parsing. There is ample evidence that the LMTL supports syntactic combination[20-23]. For example, the left pMTG in verb-noun combination shows the strongest model fit in the left middle temporal gyrus[21], and both noun and verb phrases (e.g., "the frightened boy" and "frightened the boy") inducing greater activity in the superior temporal sulcus compared to word lists[22]. Moreover, post-nominal adjective-noun composition correlates with activity in the left medial to posterior temporal lobe when semantics is held constant[23].

Our findings also align well with the controlled semantic cognition (CSC) framework[42], which proposes a functional dissociation of the anterior and middle temporal regions. Under this framework, the ATL integrates information from different sources into a coherent concept, whereas the posterior middle temporal gyrus (pMTG) retrieves and manipulates semantic knowledge. Evidence for this functional dissociation comes from studies on semantic disorders showing different patterns of impairment: patients with focal ATL atrophy exhibit symptoms of semantic dementia (SD), with performance strongly influenced by concept familarity[43]. In contrast, patients with temporoparietal damage are usually diagnosed with semantic aphasia (SA), characterized by their deficits in controlled semantic retrieval[44], such as retrieving infrequent semantic associations. Mirroring the two patients' profiles, we also observed the LATL activation for semantically related word pairs, and the LMTL response to infrequent semantic associations. We additionally demonstrate that compositionality interacts with semantic association, supporting a crucial role of syntactic knowledge in semantic cognition, and vice versa.

At the temporal dimension, the regression analysis showed a slightly earlier LATL activity compared to the LMTL activity with a largely overlapping time window from 650-800 ms, replicating previous findings that composition occurs around 180-250 ms after the onset of the second word[1,2,5]. The time periods for significant decoding performance within the two regions were a bit later at around 850-930 ms period. Crucially, the LATL and LMTL activity did not differ much in the time domain across the regression and decoding analysis. The pattern-based

directed analysis, however, revealed that activity originated in the LATL 600 ms before it was continuously delivered to the LMTL within 300 ms after the stimulus onset, suggesting a prominent information flow from the LATL to the LMTL. The LATL and the LMTL have been shown to be functionally connected during semantic association judgements[45], and the LATL was assumed to connect to the LMTL among other modality-specific regions under the "hub-and-spoke" model of semantic cognition[46]. Our results provide novel evidence on the direction of the functional connection between the LATL and the LMTL. Our regression and decoding analyses showed that the LATL is more sensitive to the high-associative compositional phrases while the LMTL is responding to the low-associative compositional phrases. The information flow from the LATL to the LMTL further suggests that high-associative composition precedes low-associative composition. We interpreted these results as reflecting a functional dissociation where the LATL supports "shallow" meaning composition of common phrases, while the LMTL is engaged to interpret novel phrases via syntactic composition. At the temporal dimension, "shallow" meaning formation occurs earlier in the LATL, and triggers syntactic composition in the LMTL when the complex meaning is unfamiliar.

The interaction of composition and association in the left temporal lobe offers insight into the relation between compositional and distributional semantics, which has been the subject of much discussion in natural language processing and cognitive science. Distributional semantic models work by building co-occurrence vectors for every word in a corpus based on its context. They provide concrete information of word meaning but do not scale up to larger constituents of text, such as phrases or sentences. Compositional formal semantics complements this approach and various models have been proposed to combine the two paradigms[47,48]. These models typically contain one uniform operator such as addition or multiplication for all compositional phrases. Here we showed that the LATL and LMTL respond differently to high- and low-associative compositional phrases, suggesting different neural substrates and potentially different neural mechanisms for combining constituents with different associative strength.

In summary, we show evidence for distinct profiles in the left temporal lobe where the LATL is mostly sensitive to high-associative compositional phrases, while the LMTL responds more to low-associative compositional phrases. We also observed a prominent information flow from the LATL to the LMTL, suggesting that the integration of adjective and noun properties originated earlier in the LATL is consistently delivered to the LMTL when the complex meaning is newly encountered.

Methods

Experiments and participants. We conducted two variates of experiment, both employed a 2 by 2 design with associative strength (Low, High) and compositionality (Comp, List) as factors. In the first experiment, there are 60 trials for each of the 4 conditions and 60 single word controls consisted of 5 "x"s and the food noun (e.g., "xxxxx cheese"), forming a total of 300 unique trials. In the second experiment, each condition contains 45 trials and 45 single word controls, forming a total of 360 unique trials. The single word trials consisted of length-matched consonant strings and the food noun (e.g., "xjtgbv cheese"; see Fig. 1a). The full stimuli set is shown in Supplementary Table 1.

Participants were healthy young adults with normal hearing and normal or corrected-to-normal vison. All strictly qualified as right-handed on the Edinburgh handedness inventory[49]. They self-identified as native English speakers and gave their written informed consent prior to participation, in accordance with New York University and New York University Abu Dhabi IRB

guidelines. 30 volunteers participated in Experiment 1, 9 of them were removed from data analysis: 8 due to excessive movement or drowsiness during MEG recording, and 1 due to bad performance on the behavioral task (less than 75% accuracy). 26 volunteers participated in Experiment 2, 5 of them were removed from data analysis: 4 due to excessive movement or drowsiness during MEG recording, and 1 due to bad performance on the behavioral task. Therefore, a total of 42 participants (24 female, mean age=22.3 years, SD=6.3) were included in the analyses. No participant attended both experiments.

Experiment 1 was conducted at the Neuroscience of Language Lab at New York University Abu Dhabi, and Experiment 2 was conducted across research facilities of the Neuroscience of Language Lab at New York University and New York University Abu Dhabi. 8 participants' data were collected at the New York facility.

Experiment procedures. Each trial was presented once followed by an image in pseudorandom order, constrained such that the image matched for half of the trials. The target words were presented using PsychoPy[50] for 300 ms each, in white 30-point Courier font, on a gray background. A blank screen was presented for 300 ms between words and images. The inter-trial interval was normally distributed with a mean of 400 ms (SD=100ms). After target words were shown, an image appeared on screen and remained until subjects indicated whether it was a Match or a Mismatch to the preceding phrase, by pressing a button with either the index or middle finger of their left hand (see Fig. 1a for trial structure). No feedback was provided. Order of stimulus presentation was pseudo-randomized such that half of the trials were a Match and the other half a Mismatch. Each participant received a unique randomisation. Images for the categorization task were chosen to encourage concentration on both country nouns/adjectives and food nouns. All images were color photographs found on Google Images.

Before recording, each subject's head shape was digitized using a Polhemus dual source handheld FastSCAN laser scanner (Polhemus, VT, USA). Participants then completed the experiment while lying supine in a dimly lit, magnetically shielded room. At the Abu Dhabi facility, MEG data were recorded continuously using a whole-head 208 channel axial gradiometer system (Kanazawa Institute of Technology, Kanazawa, Japan); at the New York facility, MEG data were collected using a whole-head 156-channel axial gradiometer system (Kanazawa Institute of Technology, Kanazawa, Japan). Stimuli were projected onto a screen approximately 50 cm away from the participants' eyes. The recording session, including preparation time and practice, lasted around 40 minutes.

MEG data acquisition and pre-processing. MEG data were recorded continuously at a sampling rate of 1000 Hz with an online 1 Hz high-pass filter and 200 Hz low-pass filter. The raw data were first noise reduced via the Continuously Adjusted Least-Squares Method[51] and low-pass filtered at 40 Hz. Independent component analysis (ICA) was then applied to remove artifacts such as eye blinks, heart beats, movements, and well-characterized external noise sources. The MEG data were then segmented into epochs spanning 100 ms pre-stimulus onset to 1200 ms following, and baseline corrected relative to the initial 100 ms pre-stimulus interval. Epochs containing amplitudes greater than an absolute threshold of 2000 fT were automatically removed. Additional artefact rejection was performed through manual inspection of the data, removing trials that were contaminated with movement artefacts or extraneous noise. The whole epoch rejection procedure results in an average rejection rate of 9.4% (SD=6.5%) for each participant.

Cortically constrained minimum-norm estimates[52] were computed for each epoch for each participant. To perform source localization, the location of the participant's head was coregistered with respect to the sensor array in the MEG helmet. For participants with anatomical MRI scans (n=5), this involved rotating and translating the digital scan to minimize the distance between the fiducial points of the MRI and the head scan. For participants without anatomical scans, the FreeSurfer[53] "fsaverage" brain was used, which involved first rotation and translation and then scaling the average brain to match the size of the head scan. A source space of 2562 source points per hemisphere was generated on the cortical surface for each participant. The Boundary Element Model (BEM) was employed to compute a forward solution, explaining the contribution of activity at each source to the magnetic flux at the sensors. Channel-noise covariance was estimated based on the 100 ms intervals prior to each artifact-free trial. The inverse solution was computed from the forward solution and the grand average activity across conditions. To lift the restriction on the orientation of the dipoles, the inverse solution was computed with "free" orientation, meaning that the inverse operator places three orthogonal dipoles at each location defined by the source space. When computing the source estimate, only activity from the dipoles perpendicular to the cortex were included. For each trial within one condition, the same inverse operator for that condition was applied to yield dynamic statistical parameter maps (dSPM) units[54] using an SNR value of 3. All data preprocessing steps were performed with MNE-python (v.0.19.2)[55] and Eelbrain (v.0.25.2)[56].

Quantifying semantic associations. Semantic vectors for the country and food words were derived using the well-known GloVe word embeddings model[17] trained on Common Crawl, which contains petabytes of raw web page data, metadata extracts and text extracts. GloVe model embodies the ''distributional hypothesis'' that words with similar meaning occur in similar contexts in an artificial neural network approach. The GloVe word vectors are freely available at https://nlp.stanford.edu/projects/glove/. Having obtained a 300-dimensional vector for each word, we then quantified how semantically associated each country word was to the food word by calculating the cosine similarity score between the two word vectors. Overall, our approach generated high associative phrases (e.g., "French/France cheese") with a cosine similarity score greater than 0.3 and low associative pairs (e.g., "Korean/Korea cheese") with a cosine similarity score lower than 0.15. Fig. 1b visualizes all the word embeddings on a 2D scatter using t-SNE[57].

Behavioral data analysis. We applied linear mixed effect model to the accuracy and reaction times (RTs) of participants' responses to the picture-matching task, with fixed effects for association and composition (with the interaction term), and a random intercept for subjects. To control for the word frequency effect, we also included the frequency of the first and second word as fixed effects:

$$\text{RT/accuracy} = \text{word1_frequency} + \text{word2_frequency} + \text{association} \times \text{composition} + (1|\text{subject})$$

Word frequency was calculated based on the combined word counts from the Google Book unigrams[58] and the SUBTLEXus corpus[59]. RTs above or below than 3 standard deviations were removed under the assumption that these represented errors or distractions rather than task-related responses. Word frequencies and RTs were log-transformed. Visual inspection of residual plots did not reveal any obvious deviations from homoscedasticity or normality. P-values were obtained by likelihood ratio tests of the full model with the effect in question against the model without the effect in question.

Mass univariate multiple regression. In order to maximize statistical power and account for extraneous variation, we coded conditions as binary variables and performed a two-stage regression analysis (Fig. 3a). At the first stage, we applied an ordinary least squares regression for each participant's single-trial source estimates for each source within a bilateral language mask at each timepoint of the whole 1300 millisecond time window. The language mask covered regions including the temporal cortex, the inferior frontal gyrus (LIFG; defined as the combination of BAs 44 and 45), the ventromedial prefrontal cortex (vmPFC; defined as BA11), the angular gyrus (AG; defined as BA39) and the supramarginal gyrus (SMA; defined as BA 40). The design matrix for the regression model included association strength and compositionality with their interaction, and the control variables (the first and second word frequency). This resulted in a β coefficient for each variable at each source and each timepoint for each subject.

At the second stage, we performed a one-sample t-test on the distribution of β values across subjects for each variable separately, again at each source and each timepoint, to test if their values were significantly different from zero. The t-tests are one-tailed such that t-values with the same polarity are clustered together as separate regions. Clusters were then formed based on the t-values that were contiguously significant through time and space, at a level of $p < .05$. Only clusters that contained a minimum of 10 sources and spanned at least 10 ms were entered into a cluster-based spatiotemporal permutation test[31] This involved randomly shuffling 0 and the β coefficient for each participant, repeating the mass univariate one-sample t-test and cluster formation within the 0-1200 ms analysis window. This procedure was performed 10,000 times, resulting in a distribution of 10,000 cluster-level statistics. Each of the observed clusters was subsequently assigned a *p*-value based on the proportion of random partitions that resulted in a larger test statistic than the observed one. The center of mass for each spatiotemporal cluster in Montreal Neurological Institute (MNI) coordinates was calculated by weighting the position of each constituent source by its mean t-value over the time window of the cluster.

Multivariate pattern classification. We performed the multivariate pattern classification in the LATL and LMTL fROIs derived from the univariate multiple regression analysis. We selected the most responsive sources in the two fROIs at a threshold of $|t| > 1$. This resulted in an LATL fROI with 161 sources, and an LMTL fROI with 108 sources. The general analysis pipeline comprised of preprocessing, data partitioning and classification steps. In preprocessing, we first down-sampled the single trial source estimates by averaging across 5 consecutive milliseconds bins. We then combined the trials in each condition to 15 pseudo-trials by randomly dividing the trials into 15 partitions and averaging across the trials within partitions. These two steps were performed to decrease the computational costs and increase the signal-to-noise ratio. The resulting data pattern for one pseudo trial in the association x composition fROI is a 161 (number of sources) x 206 (number of down-sampled timepoints) matrix, and the data for one pseudo-trial in the composition fROI is a 108 x 206 matrix. We further applied a multivariate noise normalization[37] to the pseudo trials, where the data pattern x was normalized by means of a covariance matrix Σ: $x^* = \Sigma^{-\frac{1}{2}} x$. The covariance matrix Σ was computed on the full time points of the data.

After preprocessing, we trained 4 linear Support Vector Machine (SVM) classifiers, each applied to a pairwise combination of the 4 conditions: high-associative phrases vs high-associative lists, low-associative phrases vs low-associative lists, high-associative phrases vs low-associative phrases, and low-associative phrases vs low-associative lists. Linear SVM classifier was chosen as it has been shown to out-perform other classifiers on both MEG[37] and fMRI data[38]. We performed a leave-one-stimulus-pair-out cross-validation procedure, where one randomly selected

pseudo-trial was taken from each condition as a test sample and all remaining stimuli were used for classifier training. 100 randomized assignments of trials to pseudo-trials and cross-validation folds were applied with the randomly selected left-out pairs of pseudo-trials. Classifier performance was estimated by averaging across the 100 permutations. The binary classifiers were separately applied to all timepoints. The regularization parameter C of the classifiers was selected by grid search in the range of $C = 2^{-5}$ to 2^{15} using five-fold cross-validation within the training data.

The same analysis pipeline was applied to each subject. Classification accuracy averaged over subjects at each timepoint minus the chance level of 50% was submitted to a one-sample t-test with 10,000 permutations. The permutation test window was between 600-1200 ms. We used the python scikit-learn package (0.22.1) for the SVM analyses.

Directed connectivity analysis. To understand how information is transferred between the LATL and the LMTL fROIs, we conducted a pattern-based directed connectivity analysis[21,30,31] between the two regions. The underlying logic is similar to that of the Granger causality analysis[39], namely, if the activity in region A has a causal effect on the activity in region B, then activity at a past time point of region A should contain information that helps predict current activity in region B above and beyond the previous activity in region B alone. We first calculated the data representational dissimilarity matrices (RDMs) of the two fROIs at time point D(A, t) and D(B, t) as 1 minus the pairwise Pearson r's correlation among the conditions (Fig. 3c). To increase the signal-to-noise ratio, we adopted the same preprocessing procedures in the MVPA analysis, including downsampling the source estimates by averaging across 5 consecutive milliseconds bins and combining the trials in each condition to 15 pseudo-trials. We then quantified the directed activity from region A to region B as the partial correlation coefficient between D(A, t-dt) and D(B, t), partialling out D(B, t−dt), where dt is the time interval between the current time point and the previous time point. We computed the directed connectivity from region A to region B and from region B to region A for each time points from the onset of the second word (600 ms after the onset of the first word) to the following 600 ms (1200 ms after the onset of the first word), with a dt value ranging from 5 ms to 600 ms. The same procedure was applied to each subject to obtain an average partial correlation coefficient matrix (Fig. 3c). Significance was determined by 10,000 nonparametric cluster-based permutations with a cluster-wise $p < .05$.

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Author contributions
J.L. and L.P. designed research. J.L. performed research and analyzed data. J.L. and L.P. wrote the paper.

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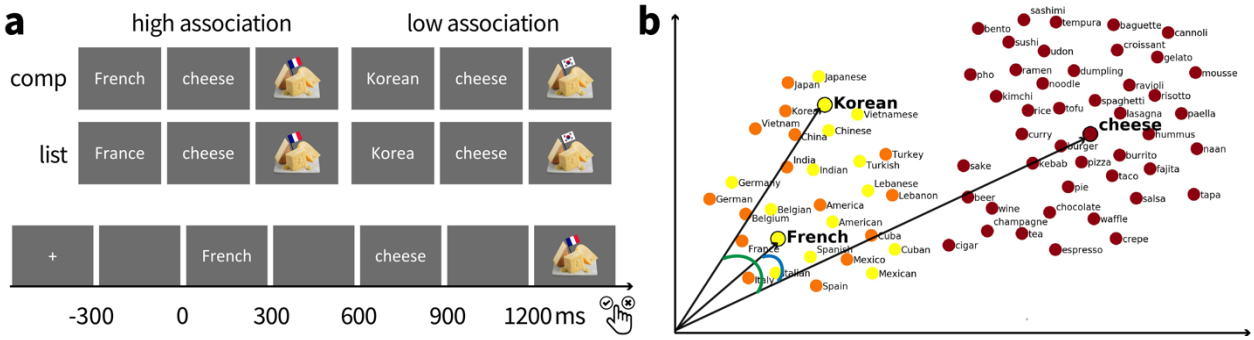


Fig. 1 Experimental design. **a** Experimental design and trial structure. Our design crossed strength of association (Low vs High) and compositionality (List vs Comp). In each trial, participants indicated whether the target picture matched the preceding words. Half of the target pictures matched and half did not. Activities recorded from 100 ms pre-stimuus onset to 1200 ms post-stimulus onset were analyzed. **b** Schematic diagram showing how cosine value between high-dimensional vectors represents semantic similarity. The smaller the angle is between two vectors, the higher the cosine value and semantic similarity. The angle between "French" and "cheese" is smaller than the one between "Korean" and "cheese" because they share more contextual features. The high-dimensional word embeddings were visualized on the 2D scatter using t-Distributed Stochastic Neighbor Embedding (t-SNE)[57].

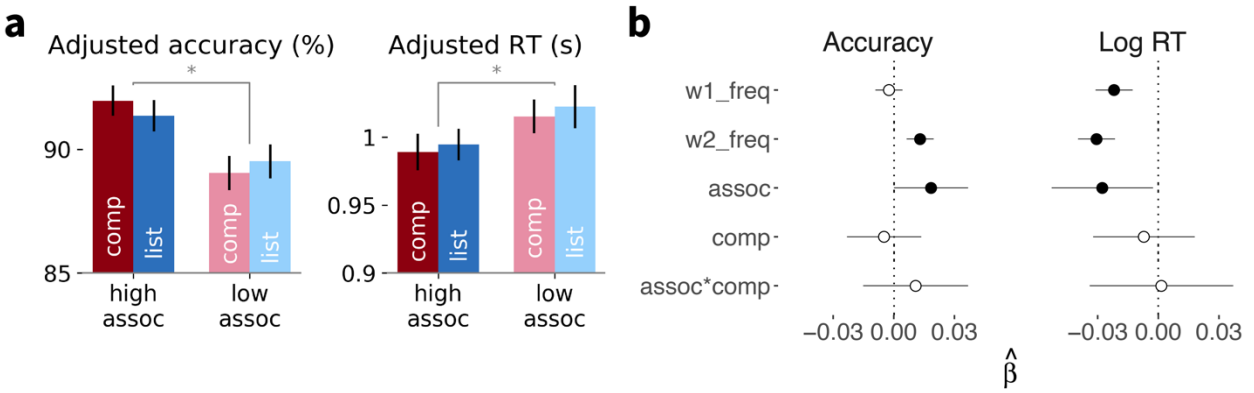


Fig. 2 Behavioral results. **a** Mean predicted accuracy and reaction time for the four conditions, regressing out the effect of word frequency. Association is a significant predictor for both accuracy (p=0.049) and reaction time (p=0.03). Error bars indicate 1 standard error. * p<.05**. b** Fitted coefficients for all predictors for accuracy and log reaction time. Error bars show 95% confidence intervals. Filled points indicate statistically significant coefficients at the level of p<.05.

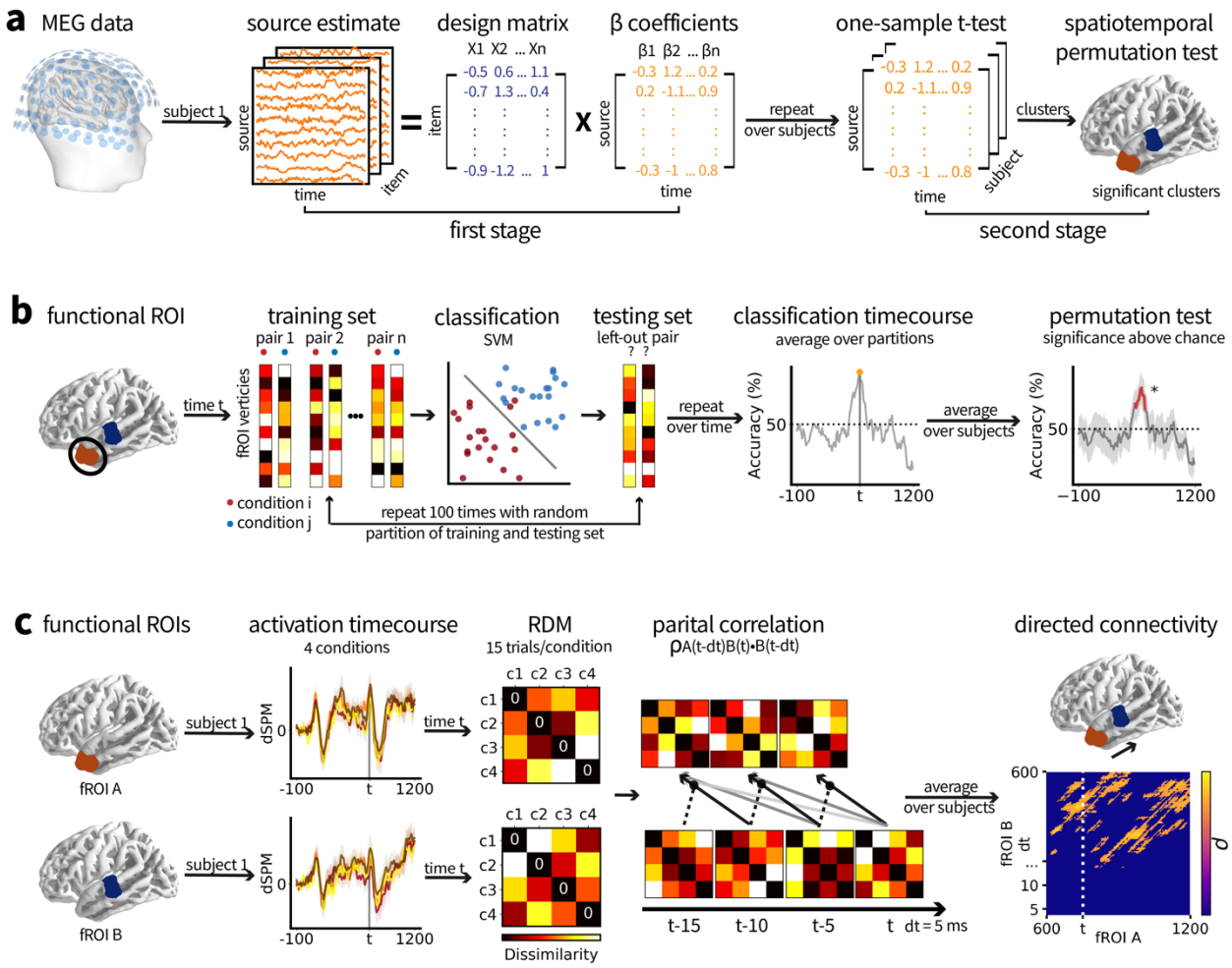
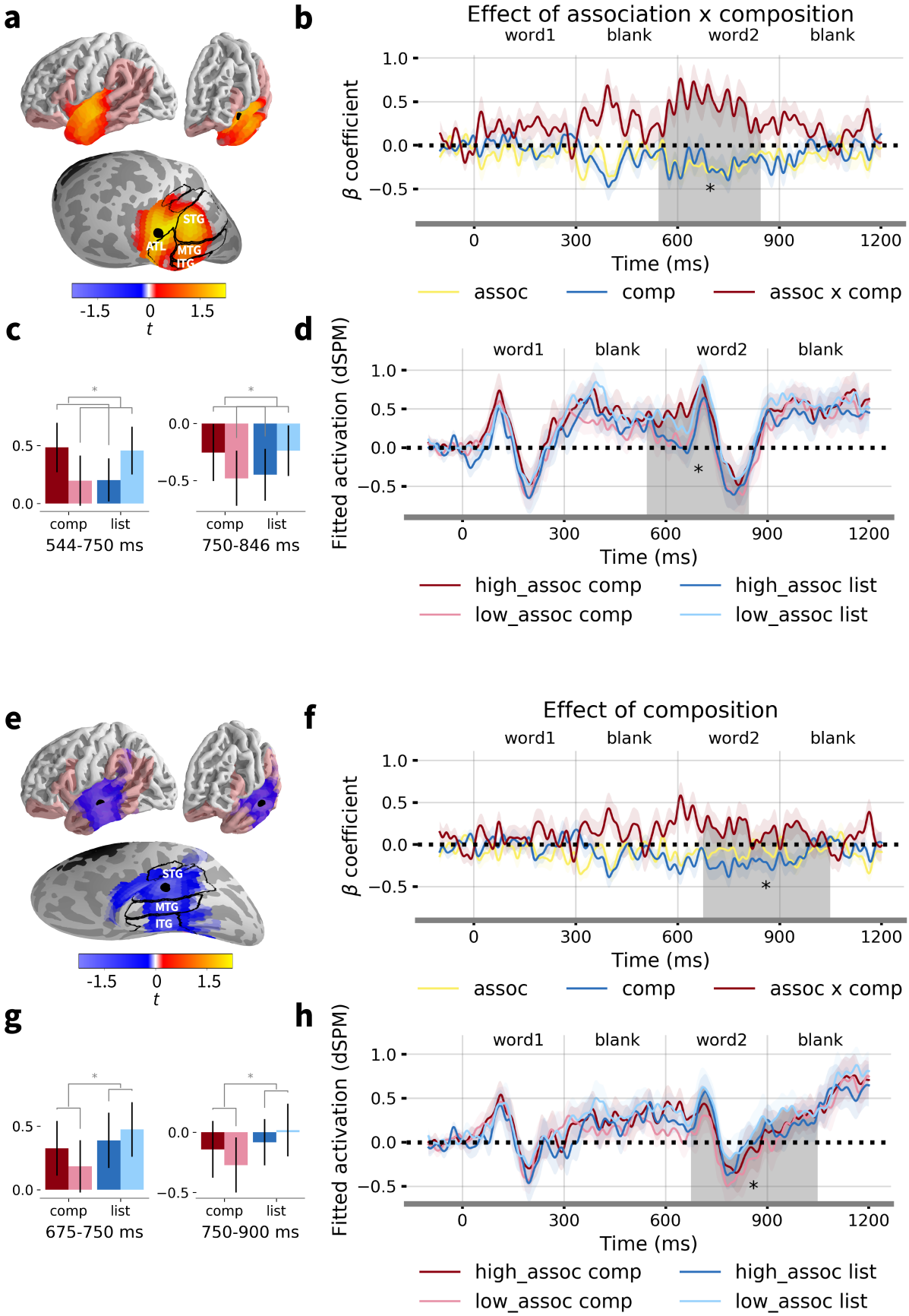


Fig. 3 Schematic illustration of the analysis procedure. **a** Two-stage multiple regression analyses. At the first stage, an ordinary least squares regression was applied to each participant's single-trial source estimates for each source within a selected region at each timepoint of the analysis window. At the second stage, a one-sample t-test was performed on the distribution of β values across subjects for each variable at each source and each timepoint, to test if their values were significantly different from zero. The significant clusters were determined by a cluster-based spatiotemporal permutation test[33] with 10,000 permutations. **b** Multivariate pattern classification analyses. A linear Support Vector Machine (SVM) was trained on the combination of pseudo-trials from 2 conditions and tested on a left-out pair with 100 permutations. The same SVM analysis was applied independently to each timepoint and for each subject. Classification accuracy averaged over subjects at each timepoint minus the chance level of 50% was submitted to a cluster-based one-sample t-test with 10,000 permutations. **c** Directed connectivity analyses. The representational dissimilarity matrices (RDMs) of the source estimates of the two fROIs at time point t, D(A, t) and D(B, t), was calculated as 1 minus the correlation between the conditions. Directed activity from region A to region B was quantified as the partial correlation coefficient between D(A, t-dt) and D(B, t), partialling out D(B, t−dt), where dt is the time interval between the current time point and the previous time point. Significance of coefficients greater than 0 was determined by 10,000 nonparametric cluster-based permutations with a cluster-wise $p < .05$.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b
Effect of association x composition
word1
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word2
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β coefficient
1.0
0.5
0.0
−0.5
0
300
600
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1200
Time (ms)
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comp
assoc x comp
c
0.5
0.0
comp
list
544-750 ms
0.0
−0.5
comp
list
750-846 ms
d
Fitted activation (dSPM)
word1
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word2
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Time (ms)
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low_assoc comp
low_assoc list
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ITG
-1.5
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Effect of composition
word1
blank
word2
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β coefficient
1.0
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0.0
−0.5
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comp
list
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0.0
−0.5
comp
list
750-900 ms
h
Fitted activation (dSPM)
word1
blank
word2
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0.5
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−0.5
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Time (ms)
high_assoc comp
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low_assoc comp
low_assoc list

Fig. 4 Multiple regression results. **a** Location of the significant cluster sensitive to the interaction effect between association and composition derived from the spatiotemporal cluster test. Light red regions mark the language network within which the analysis was conducted. Black dot indicates location of peak activity at the latency of 608 ms. Color bar indicates t-statistics. **b** Timecourses of β coefficients for association, composition and their interaction term averaged over the cluster. **c** Fitted responses for each condition averaged over the cluster and time windows for the positive and negative polarity peak. **d** Timecourses of fitted response for each condition averaged over the cluster. Word frequency effects were regressed out of the responses. Shaded region indicates the significant time window from 544-846 ms. **e** Responses for each condition time-locked to the interaction effect in the peak cluster, averaged over the time window of 544-750 ms for positive polarity and of 750-846 ms for negative polarity. **e** Location of the significant cluster sensitive to the composition effect derived from the spatiotemporal cluster test. Black dot indicates location of peak activity at the latency of 860 ms. **f** Timecourses of β coefficients for association, composition and their interaction term averaged over the cluster. **g** Fitted responses for each condition averaged over the cluster and the time windows for the positive and negative polarity peak. **h** Timecourses of fitted response for each condition averaged over the cluster. Word frequency effects were regressed out of the responses. Shaded region indicates the significant time window from 675-1050 ms. * $p < .05$. STG: superior temporal gyrus; MTG: middle temporal gyrus; ITG: inferior temporal gyrus; ATL: anterior temporal lobe.

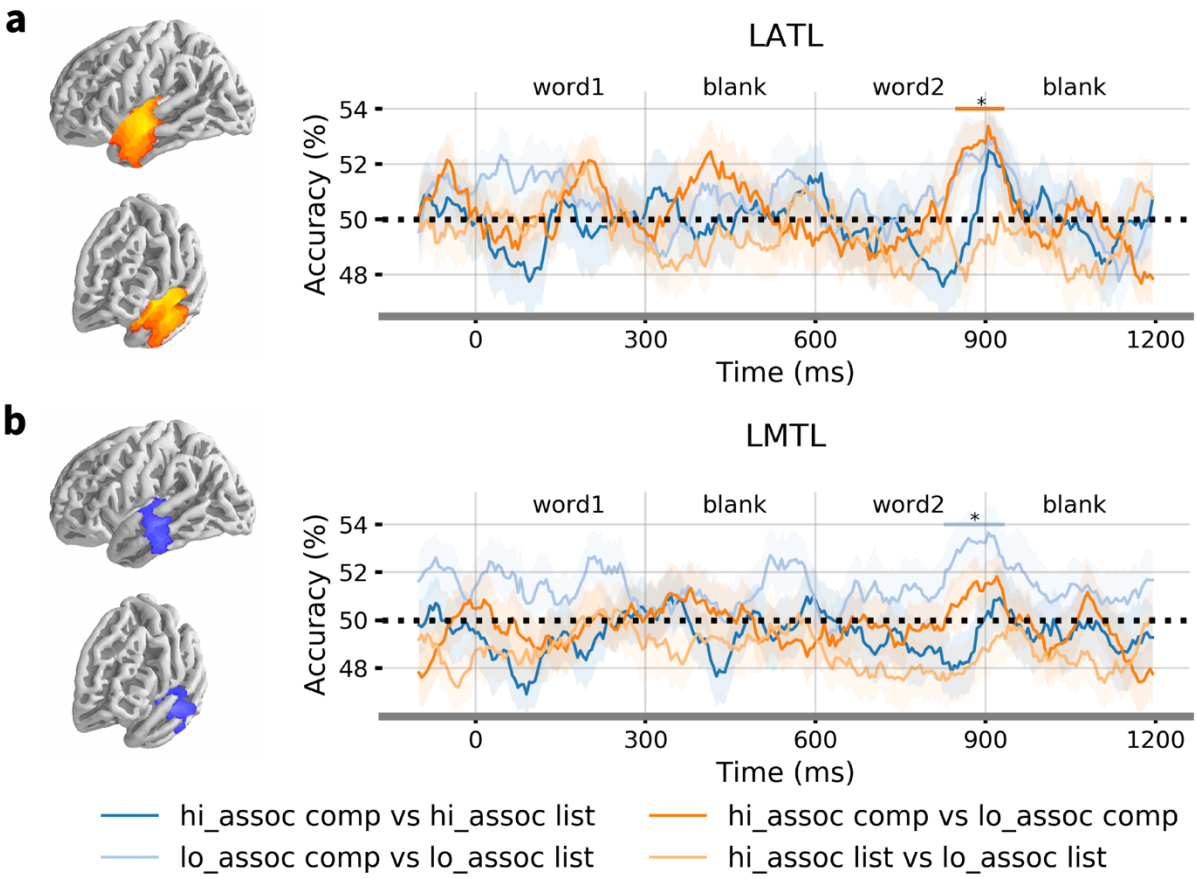

Fig. 5 Multivariate pattern classification results. **a** Color-coded curves report classification timecourses for the 4 linear SVM classifiers within the functional ROI (thresholded at $|t| > 1$) for the interaction effect between association and composition identified by the regression analyses. Horizontal lines above the curves mark a statistically significant time window from 850-935 ms for the high-associative composition vs low-associative composition classifier ($p=0.019$). **b** Classification timecourses for the 4 linear SVM classifiers within the functional ROI for the composition effect identified by the regression analysis. Horizontal line above the curves marks a significant time window from 830-935 ms for the low-associative composition vs low-associative list classifier ($p=0.035$). Significance over the

chance level of 50% was assessed by a cluster-based permutation *t*-test within the analysis window of 600-1200 ms. * p < .05.

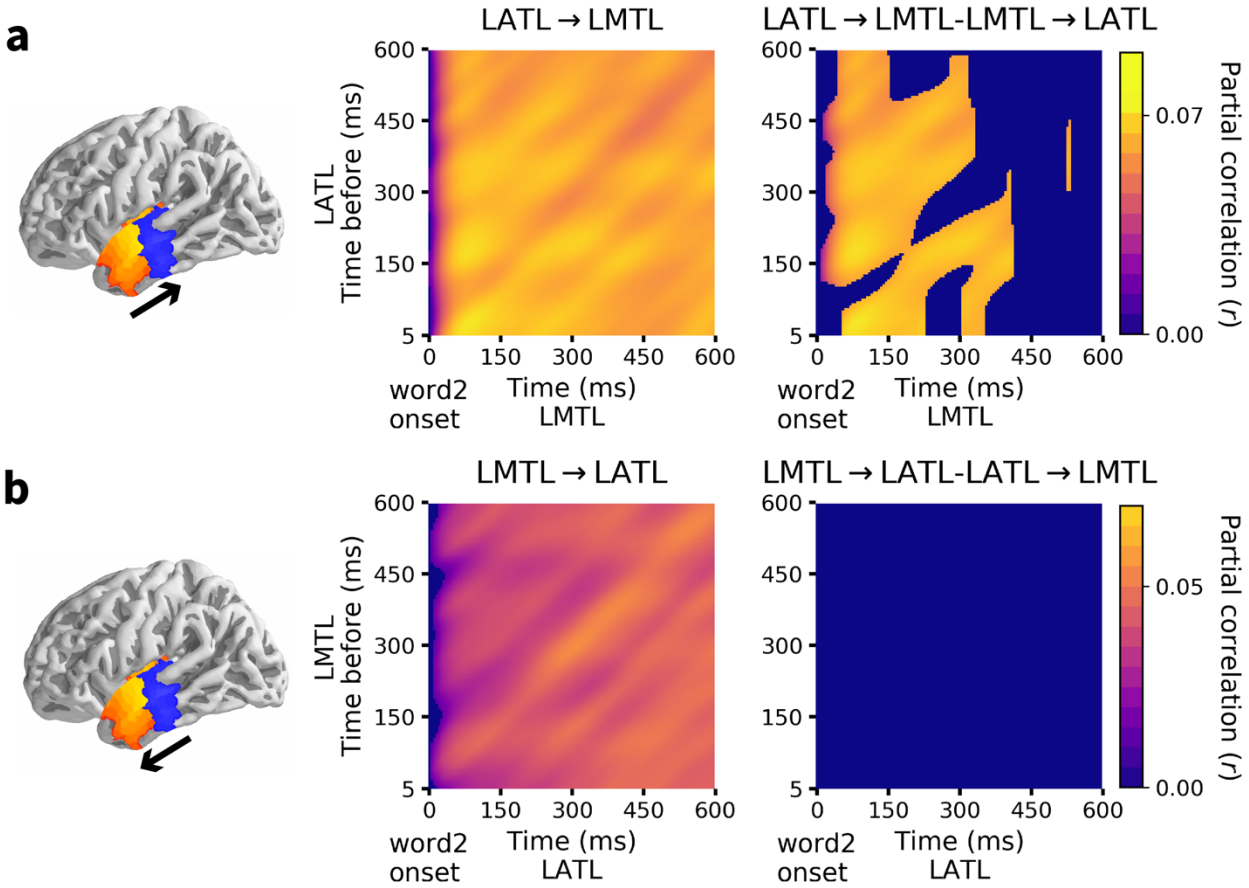

Fig. 6 Directed connectivity between the LATL and the LMTL. **a** Significant partial correlation coefficients matrix from LATL to LMTL. Contrast between the two directed connectivity measures show significant correlations from LATL to LMTL from 0 to 300 ms after the onset of the second word, with a delay from 5-600 ms. **b** Significant partial correlation coefficients matrix from LMTL to LATL. Contrast between the two directed connectivity measures show no significant correlations from LMTL to LATL.