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The role of left angular gyrus in the representation of linguistic composition relations

Wenjia Zhang^{1,2} | Ming Xiang³ | Suiping Wang¹

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¹Philosophy and Social Science Laboratory of Reading and Development in Children and Adolescents (South China Normal University), Ministry of Education, Guangzhou, China

²School of Psychology, South China Normal University, Guangzhou, China

³Department of Linguistics, University of Chicago, Chicago, Illinois, USA

Correspondence

Suiping Wang, Philosophy and Social Science Laboratory of Reading and Development in Children and Adolescents, South China Normal University, Ministry of Education, Guangzhou, China.

Email: wangsuiping@m.scnu.edu.cn

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Abstract

Language comprehension is compositional: individual words are combined structurally to form larger meaning representations. The neural basis for compositionality is at the center of a growing body of recent research. Previous work has largely used univariate analysis to investigate the question, a technique that could potentially lead to the loss of fined-grained information due to the procedure of averaging over neural responses. In a functional magnetic resonance imaging experiment, the present study examined different types of composition relations in Chinese phrases, using a 1-back composition relation probe (CRP) task and a 1-back word probe (WP) task. We first analyzed the data using the multivariate representation similarity analysis, which better captures the fine-grained representational differences in the stimuli. The results showed that the left angular gyrus (AG) represents different types of composition relations in the CRP task, but no brain areas were identified in the WP task. We also conducted a traditional univariate analysis and found greater activations in the bilateral inferior frontal gyrus in the CRP task relative to the WP task. We discuss the methodological and theoretical implications of our findings in the context of the larger language neural network identified in previous studies. Our findings highlight the role of left AG in representing and distinguishing fine-grained linguistic composition relations.

KEYWORDS

angular gyrus, composition, compositionality, language comprehension, multivariate RSA

INTRODUCTION 1

Humans' amazing expressive power arises from a fundamental feature of natural language: compositionality. Humans can combine smaller linguistic units into larger structured representations and compose meaning based on how individual pieces are combined. The meaning of a sentence is more than just the sum of the individual words contained in the sentence. Depending on how the words are combined, semantic meaning is derived from an abstract hierarchical

structure. In theory, one can make a distinction between the combinatoric mechanism at the syntactic level and at the semantic level. In practice, however, it is difficult to strictly separate the cognitive processes that support structure building and those that support semantic composition, because for the most part the latter tracks the former. In this article, we use the term compositionality in a broad sense, referring to the general combinatoric process underlying language comprehension. Our goal is to examine the neural basis of compositionality.

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WILEY 2205 mentioned above, using the functional magnetic resonance imaging

Previous studies using a variety of different paradigms have revealed a network of brain areas involved in sentence processing. A number of studies compared structured sentences with controls that were Jabberwocky sentences or completely unstructured word lists. Jabberwocky sentences are constructed by replacing the meaningful content words of a sentence with nonwords, while retaining the functional words of a grammatical sentence. These studies revealed that inferior frontal gyrus (IFG), angular gyrus (AG), and posterior superior temporal areas were most involved in the sentence-level composition (Fedorenko, Nieto-Castañón, & Kanwisher, 2012; Matchin, Hammerly, & Lau, 2017; Pallier, Devauchelle, & Dehaene, 2011). Scott and colleagues examined speech and speech-like stimuli with equivalent acoustic complexity but varying intelligibility, and showed that anterior superior temporal sulcus (STS) is responsive to intelligible stimuli (Scott, Blank, Rosen, & Wise, 2000; Scott, Rosen, Lang, & Wise, 2006). Rodd, Davis, and Johnsrude (2005) compared sentences containing ambiguous words and those with low ambiguity. Their results showed that complex sentences (i.e., those with ambiguity) elicited increased activation in left posterior inferior temporal cortex and IFG bilaterally.

The findings of these earlier studies significantly enhanced our understanding of the brain basis of natural language comprehension. However, because these studies often targeted the comprehension process at the sentence level, the brain network revealed from these studies is likely to be responsible for more than just the composition or the combinatorial process. During sentence comprehension, comprehenders not only need to combine words, but they also need to maintain syntactic and semantic relations between nonadjacent elements, keep track of different referents introduced by the sentence, evaluate the overall plausibility of the sentence meaning against their world knowledge, and accommodate any pragmatic inferences a sentence may trigger. All of these processes could have affected the results observed from sentence comprehension studies.

To more precisely isolate the compositionality process in the brain, a number of studies looked more narrowly at the level of simple phrases. For example, in a number of magnetoencephalography (MEG) studies, Pylkkänen and colleagues examined how two words integrated to make a meaningful phrase (Bemis & are Pylkkänen, 2011; Pylkkänen, 2019). In these studies, target words were either preceded by adjectives in the combinatory condition (e.g., red boat) or by unpronounceable consonant strings in the noncombinatory condition (e.g., xkg boat). The comparison between these conditions suggested that the composition process mainly takes place in the left anterior temporal lobe (LATL) and ventral medial prefrontal cortex (vmPFC; Bemis & Pylkkänen, 2011, 2013). Moreover, the composition effect in the LATL was found both in reading and listening (Bemis & Pylkkänen, 2012) and in production (Pylkkänen, Bemis, & Elorrieta, 2014), suggesting a modality-independent function (Pylkkänen, 2020). Consistent with this, a more recent MEG study also found the involvement of the LATL in the composition process, but this was accompanied by composition-related activation in the left AG and posterior temporal lobe (Flick, Abdullah, & Pylkkanen, 2021). In addition, although the left IFG was not implicated in the MEG result

(fMRI) technique, Zaccarella and colleagues found that left pars opercularis in IFG was more activated in the phrasal syntactic context (e.g., this flirk) than in the list context (e.g., apple flirk), suggesting the role of left IFG as well in housing the composition processes (Zaccarella & Friederici, 2015; Zaccarella, Meyer, Makuuchi, & Friederici. 2017).

Almost all the studies discussed above used univariate analysis as their primary analytical tool. The univariate analysis compares the neural activation of a group of stimuli from one condition with the neural activation of a group of stimuli from another condition, by averaging over the neural responses across a large number of voxels in a region of interest. The averaging procedure could lead to loss of fine-grained information. Moreover, univariate analysis guantifies activation by measuring the relative difference between conditions. However, it is possible that the activation differences between two conditions could arise from cognitive processes beyond the immediate target of interest (Blanco-Elorrieta, Kastner, Emmorey, æ Pylkkänen, 2018). For instance, if a brain region is found to respond more strongly to meaningful phrases than word lists, it is possible that the brain region is responding to representational differences between the two conditions, that is, one involves composition and the other does not. It is also possible, however, that the two types of stimuli evoked different general cognitive demands (e.g., demands in attention, working memory, etc.), and that is what the brain region is responding to. Similarly, if multiple brain areas are found to respond to one condition more strongly than the other, it is difficult to precisely identify a functional interpretation for each brain area. To address some of the limitations of univariate analysis, the current study applied representation similarity analysis (RSA) to study the compositionality process underlying language comprehension.

RSA is a type of multivariate data analysis method used in a growing body of neuroimaging studies (Haxby, Connolly, æ Guntupalli, 2014), which has been applied to language research on questions pertinent to resolving syntactic ambiguity (Tyler, Cheung, Devereux, & Clarke, 2013), incremental interpretation of spoken language (Lyu et al., 2019), concept processing (Carota, Kriegeskorte, Nili, & Pulvermuller, 2017), production planning in spoken and sign language (Blanco-Elorrieta et al., 2018), and so forth. In the RSA method, the representation dissimilarity matrix (RDM) is the important bridge that connects the content of experimental stimuli with neural activation patterns. A RDM is commonly a square symmetric matrix, indexed by the stimuli horizontally and vertically (in the same order). Each off-diagonal value indicates the dissimilarity of two different stimuli along a certain dimension of comparison. To conduct an RSA, normally two main RDMs are constructed. First, a target RDM is created by calculating the dissimilarity between the stimuli, along with some predefined theoretical dimensions of interest. For instance, given a set of sentences, one can ask how similar or dissimilar two sentences are in terms of the composition relation involved. The target RDM, therefore, quantifies the degree to which the two members of a pair of stimuli can be distinguished from each other along a dimension of interest. Second, a neural RDM is created by calculating

the multivariate dissimilarity between the neural activation associated with the members of each pair of stimuli. Finally, by calculating the correlation between the target RDM and neural RDMs from multiple brain regions, one can draw inferences about which brain regions best represent the information content of the stimuli. The RSA approach, therefore, does not directly map the properties of the stimuli to activations in the brain. Instead, it builds correspondence between relations among the stimuli (or the similarity structure present in the stimuli) and relations among the brain representations of the stimuli (or the similarity structure present in the brain activations; Kriegeskorte, Mur, & Bandettini, 2008).

The RSA approach is nicely suited to study how compositionality is represented in the brain, because semantic composition in natural language encompasses multiple different relations. For instance, when an adjective combines with a noun, the noun is being modified by the adjective; when a verb combines with its object noun phrase, the verb saturates the noun as one of its arguments. For the majority of the previous studies that applied the univariate method, the experimental design and the analysis procedure primarily focused on comparing a "composition" condition consisting of one single type of composition relation with a "noncomposition" condition. We know very little about whether and how the brain represents the fine details of various composition relations. An exception of this is a study from Westerlund. Kastner, Kaabi, and Pvlkkänen (2015). To address the question of whether different types of composition relation can be distinguished in the brain, this study examined phrases with different composition relations (argument saturation and predicate modification) and compared composition versus noncomposition contexts. The results showed increased responses in LATL in the composition context regardless of the composition relations, indicating similar brain responses to different types of phrases. This result, however, should not be taken as evidence that the brain is not sensitive to the fine-grained representational differences in composition relations. The univariate analysis itself may be too limited to capture the detailed brain representations of the stimuli. An additional complication with Westerlund et al. (2015) is that in their English stimuli, when the composition relation varied from one structure to another, there were also unavoidable changes in the linguistic forms, especially morphological changes associated with different word classes. It is therefore difficult to completely tease apart the effects driven by the variation of composition relations from those driven by the variation of surface forms.

The RSA method, by virtue of the fact that it is designed to map the similarity structure of the stimuli to the similarity structure of the brain representations, offers a more advanced tool to assess whether different composition relations are distinguished in the brain. In particular, a target RDM can be created based on the (dis)similarity between stimuli items in terms of the composition relation involved in each stimulus item. If a strong correlation is discovered between the target RDM and the neural RDM of a brain region, it suggests that the brain does distinguish different types of composition relation. The RSA method, with its strength in uncovering brain regions that respond to the representational content of the stimuli, provides an appealing method to study how linguistic relations are encoded in the brain.

The current study makes the first attempt to apply multivariate RSA to address the question of compositionality in language processing. The target of our case study is Mandarin Chinese. Mandarin Chinese is relatively impoverished in morpho-syntactic marking. When two words are combined, there is usually very little derivational or inflectional morphology that needs to be processed (Zhou, Ye, Cheung, & Chen, 2009). The syntactic properties of Mandarin also allowed us to construct stimuli with different composition relations while keeping a largely uniform surface form (see more detail in Section 2.2). This affords us an opportunity to better capture the brain responses sensitive to different types of composition relations, independent from the surface form. We created two-word phrases in Mandarin Chinese that instantiate four kinds of composition relations. Participants completed two different tasks, in a within-participant manipulation. In the 1-back composition relationship probe (CRP) task. participants judged whether the composition relation of the current phrase matched the preceding phrase. In the 1-back word probe (WP) task, participants judged whether one of the words in the current phrase matched a word in the preceding phrase. The CRP task explicitly asks participants to engage with the composition relation present in a phrase, whereas the WP task does not require any attention to the composition relation. If different composition relations are distinguished in the brain, the RSA should uncover brain regions that show strong correlations between the target RDM in the stimuli and the neural RDMs. Furthermore, we may expect that this effect is modulated by the experimental task. Participants are fully engaged in processing the composition relation in the CRP task, but in the WP task, they were distracted by a secondary word-identification and comparison task. Furthermore, successfully completing the WP task does not require any attention to the linguistic composition relation in the stimuli. It is therefore possible that under the WP task there is only weak or even no correlations between the target RDM and the neural RDM.

Apart from the multivariate RSA, to make a more direct comparison with the previous studies we also performed the traditional univariate analysis. The univariate analysis in previous studies was often used to compare stimuli that involved composition with stimuli that did not, but these two types of conditions are necessarily different on some lexical dimensions even after careful matching of the material. In the current study, we used identical experimental material for the CRP task and the WP task, strictly controlling for lexical differences. We first examined the significant activations and deactivations of experimental phrases > baseline in each task. We also examined brain regions that showed a significant task effect (CRP task vs. WP task) on activation. The comparison between the multivariate and the univariate analyses in the current study, together with the comparison between the current study and the previous studies, sheds light on the more precise functional interpretation of different brain regions that have been implicated in linguistic composition.

2 | MATERIALS AND METHODS

2.1 | Participants

We recruited 24 university students for the fMRI experiment. Data from four participants were excluded because of head movement (three participants, >2.5 mm) or equipment error (one participant). The remaining 20 participants (eight males, age range 18–25, mean 21.3) were right-handed native Mandarin Chinese speakers with normal or corrected-to-normal vision. No participants reported a history of neurological disorders or reading disabilities. All materials and protocols were approved by the Psychology Research Ethics Committee of South China Normal University. Written informed consent was obtained before the experiment. All participants were given a small monetary reward at the end of the study to compensate for their time.

2.2 | Materials

We constructed the experimental material based on the basic composition rules proposed in previous formal semantics work (see an overview in Pylkkänen & McElree, 2006; Pylkkanen, Brennan, & Bemis, 2011). The first rule function application applies to cases in which a predicate can serve as a function to combine with its arguments. For instance, the verb *modify* does not describe a complete event unless it saturates two individual arguments to form a meaning such as John modified the password. In this case, the verb modify first combines with its object the password via function application, and next the same rule could apply again to combine the predicate phrase modify the password with the subject John. We note that although the same general rule could either derive a verb-object or a subjectpredicate structure, as shown by the first two examples in Table 1, the noun phrases in these structures have different thematic roles. We therefore make a fine-grained distinction and treat these structures as representing different composition relations. The second general rule, predicate modification, deals with cases of modification. For example, in Table 1, by combining the words excellent and students, we form a new predicate that denotes a property of both being

 TABLE 1
 Examples of experimental phrases in four composition relations

Composition relation	Word category	Phrases
Argument saturation (subject-predicate)	Noun + adjective	(The) skirt (is) beautiful(子漂亮)
Argument saturation (verb-object)	Verb + noun	Modify (the) password(修改)
Modification (modifier- noun)	Adjective + noun	Excellent students(优 秀学生)
Modification (coordinated predicates)	Adjective + adjective	Clean (and) tidy(干净 整洁)

excellent and being a student. Similarly, after combining the words *clean* and *tidy*, a new predicate is formed that denotes the property of being both clean and tidy. Again, although the same general rule could combine an adjective and a noun, as well as combing an adjective with another adjective, given their fine-grained semantic differences, we treat these two structures as representing two kinds of composition relations. Our main analysis below created the target RDM based on the four different types of composition relations presented in Table 1. But to capture the intuition that the four relations in Table 1 could also be classified into two categories (based on the two basic rules) at a coarse level, we included additional analyses in the Supporting Information Section S3 using gradient target RDMs (also see more details below).

A total of 120 experimental phrases were created, grouped into four composition relations shown in Table 1: argument saturation between a predicate and its subject (noun-adjective), argument saturation between a verb and its object argument (verb-noun), predicate modification between an adjective and its modified noun (adjectivenoun) and predicate modification between two conjoined adjectives (adjective-adjective). There were 30 phrases for each composition relation. Each phrase consisted of two words. All the phrases were syntactically and semantically plausible and easy to comprehend. Each of the 120 experimental phrases was presented once in each task, and there were also 24 filler phrases in each task (see "Task and procedure" below).

All the phrases we used are two-word phrases (with two characters for each word). The tight control of the word length and phrase length is made possible due to some Mandarin-specific linguistic properties. For example, in Mandarin, the determiner is not required to form a noun phrase. Between a subject noun and its predicate, the linking verb (be, 是) is also not necessary. The conjunction marker "and" could also be omitted in some cases. These omittable elements are noted in parenthesis in the English translations in Table 1.

We matched the visual complexity (i.e., number of strokes in the Chinese characters), word frequency, and familiarity of experimental phrases across the four composition relations. To calculate the visual complexity of each phrase, we calculated the number of strokes in each of the four characters in each phrase and then calculated the average number of strokes across the four characters. To calculate the word frequency of each phrase, we calculated the frequency (logWCount) of each of the two words (Cai & Brysbaert, 2010) in each phrase and then calculated an average word frequency across the two words. The familiarity metric of each phase was calculated based on the familiarity ratings collected from eight additional participants who did not participate in the fMRI experiment. In the rating task, participants were asked to rate the experimental phrases on a 7-point scale, with 1 for "extremely unfamiliar" and 7 for "extremely familiar". We used the averaged rating scores across participants as the familiarity metric for each experimental phrase.

The average number of strokes in the experimental phrases in the four types of composition relations (Table 1) was 8.82 (SD = 1.41), 8.62 (SD = 1.33), 8.70 (SD = 1.77), and 8.95 (SD = 1.69), respectively. The corresponding word frequency of the experimental phrases was

26.09 (SD = 39.91), 28.78 (SD = 43.87), 31.06 (SD = 29.73), and 21.87 (SD = 23.21), respectively. The corresponding familiarity of the experimental phrases was 4.61 (SD = 0.87), 4.32 (SD = 1.39), 4.42 (SD = 0.99), and 4.85 (SD = 1.07), respectively. No significant difference was found in any of these measures across the four composition relations, Fs (3, 116) < 2, ps > .2.

2.3 | RDM construction

Six theoretical RDMs were created for the partial RSA (Figure 1). The composition relation RDM was the target RDM. The visual-pixel, semantic similarity, emotionality, imageability, and RT RDMs were the control RDMs. The composition relation RDM was created based on the combinations of the four composition relations. We constructed a square symmetric matrix, indexed by the 120 experimental phrases horizontally and vertically (in the same order). Each off-diagonal value indicates the dissimilarity of the two phrases. Phrases with the same composition relation were modeled as similar (dissimilarity = 0). In contrast, phrases with different composition relations were modeled as dissimilar (dissimilarity = 1). This RDM therefore makes a categorical distinction on whether two phrases have identical composition relation or not. As mentioned above, the four composition relations in Table 1 could also be classified into two basic categories of composition relations—argument saturation and predicate modification. Using these two general categories, in a separate analysis, we constructed a number of gradient composition relation RDMs as the target RDM. The results of these additional analyses are presented in the Supporting Information Section S3.

The control RDMs were constructed in the following way. For the visual-pixel RDM, we first created 120 figures of all the experimental phrases. The font, size, and color of the phrases were the same as they were presented in the experiment. We then read the figure of each phrase using the "imread" function implemented in MATLAB 2017a. The returned pixel matrix was further cross-correlated (using Pearson's correlation) over all 120 phrases to create a 120×120 correlation matrix. The correlation matrix was finally converted to the visual-pixel RDM (1 - *r*).

For the semantic similarity RDM, we recruited 15 participants to rate the semantic similarity of experimental phrases with a customized Matlab procedure. The phrases were first represented in a rectangle frame in random positions. Participants were asked to move each phrase to a position such that phrases with higher semantic similarity were closer together. After they achieved this aim, we extracted the *x* and *y* coordinates of each phrase. The distance matrix of these coordinates was created using standard Euclidean distances for each participant. We further averaged these distance matrices across participants as the semantic similarity RDM.

We used the emotionality RDM as a control RDM because our stimuli contained adjectives and they may trigger mental evaluations about emotions. For this RDM, we first recruited 15 participants to rate the emotionality of the experimental phrases on a 7-point scale, with 1 for "extremely unhappy" and 7 for "extremely happy". We averaged the rating scores across participants as the emotionality index of each phrase. The distance metric of these rating scores was then calculated using standard Euclidean distances to create the emotionality RDM.

We used the imageability RDM as a control RDM because verbs and adjectives usually have lower imageability scores than nouns (Bird, Howard, & Franklin, 2000; Yu, Law, Han, Zhu, & Bi, 2011). The imageability RDM in the current study was created using largely the same procedure as the emotionality RDM, with the imageability score rating measuring the difficulty/ease with which a word evokes a mental image (Caplan & Madan, 2016).

Finally, there may be variabilities across items in terms of how difficult it is to process a given item. Even for the same item, there may also be different levels of processing difficulty associated with the specific task (i.e., the CRP or the WP task). To construct an RDM that

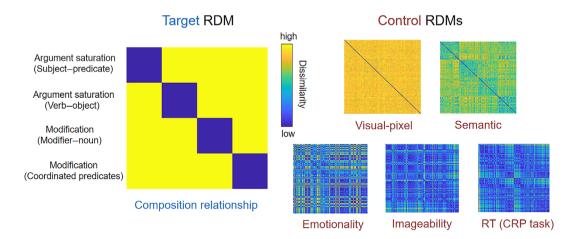


FIGURE 1 Six theoretical RDMs in the partial RSA. The target RDM is the composition relationship RDM, which is binary. The visual-pixel, semantic, emotionality, imageability, and RT RDMs are the control RDMs. The composition relations of the horizontal and vertical directions of RDMs are argument saturation (subject-predicate), argument saturation (verb-object), modification (modifier-noun), and modification (coordinated predicates). Note the RT RDM was created for each task, for simplicity, only the RT RDM in the CRP task is shown here

controls for processing difficulty, we conducted a separate behavioral experiment that used the same tasks as the fMRI experiment. The experimental material (both the target and the filler items) was identical to the fMRI experiment. The tasks and procedures were also almost identical, with the only difference being that, in the behavioral experiment, the participants were asked to press button "1" for matched phrases and button "2" for unmatched phrases. Sixteen participants were recruited for this experiment. We will report the analysis on the response accuracies (ACC) and response time (RT) in Section 3. For the purpose of constructing the RT RDM, we take the RT obtained for each item/phrase as an approximation for processing difficulty. The RTs of experimental phrases were first averaged across participants. The distance metric of the by-item RT was then calculated using standard Euclidean distances to create the RT RDM for each task.

2.4 | Task and procedure

Each participant completed two tasks in a single functional neuroimaging session. As shown in Figure 2, in the 1-back CRP task, stimuli phrases were sequentially presented to the participants, and participants were asked to press a button on a response box if the composition relation of the current phrase matched with the preceding phrase. Before the experiment, participants were given examples of each composition relation. For example, they would be presented with a "noun + adjective" phrase and were told this phrase combines a subject and a predicate; similarly an "verb + noun" phrase combines a verb with an object, an "adjective + noun" phrase combines a noun with a modifier, and an "adjective + adjective" phrase combines two adjectives. In the 1-back WP task, the overall procedure was identical to the CRP task, but the participants were asked to press the button on the response box if either word in the current two-word phrase matched a word in the preceding phrase. The position (first word or second word) of the matched word in the phrase was counterbalanced across phrases. No feedback was provided on either task. The order of the two tasks was counterbalanced across participants. Note that in the CRP task the composition relations of all the filler phrases (but none of the experimental phrases) matched the composition relation of the preceding phrase, and in the WP task the words used in all of the filler phrases (and in none of the experimental phrases) matched the words in the preceding phrase. Therefore, participants, in theory, do not need to make any response on the critical experimental trials. This ensured that the fMRI signal elicited by the experimental phrases was minimally affected by motor responses (Schomers & Pulvermüller, 2016).

We used the E-Prime 2.0 software package (Psychology Software Tools, Pittsburgh, PA) to present the stimuli and collect the behavioral response data. For each task, the 144 trials were divided into three blocks, each comprising 48 trials (40 experimental phrases and 8 filler phrases). The trials in each block were presented in a rapid event-related design in a pseudorandom sequence. The distribution of experimental and filler phrases was the same for each participant. At the beginning of each trial, a visual fixation cross was displayed on the screen (0.5 s), followed by a blank interval (0.3 s). Then a phrase was presented (2.2 s), and participants were asked to respond according to the task requirements. The Chinese characters were presented in Kai font in black against a light gray background. Finally, a blank interval (range: 3-11 s; average: 7 s) was presented as jitter time between every two trials. Each participant performed 30 practice trials to become familiarized with the procedure before the fMRI scanning.

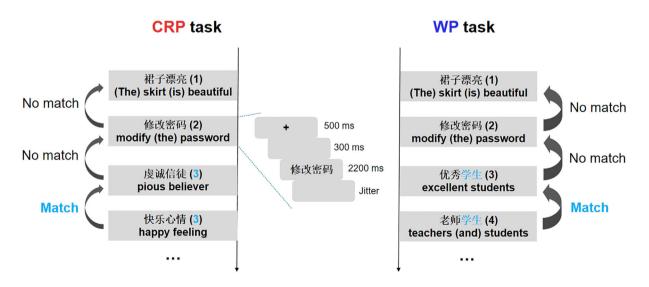


FIGURE 2 Illustration of the task and procedure. In the 1-back CRP task, the composition relations (modification) of "信" and "快乐心情" were matched. In the 1-back WP task, the word "学生" in "优秀学生" and "老师学生" was matched. The middle column shows the procedure for each trial. The number labels (1, 2, 3, and 4 in the brackets) denote the four composition relations: argument saturation (subject-predicate), argument saturation (verb-object), modification (modifier-noun), modification (coordinated predicates). Note that the number labels and English translations are for illustration. Only the Chinese phrases were presented in the fMRI experiment. CRP, composition relation probe; WP, word probe

2.5 | MRI data acquisition and preprocessing

All imaging data were acquired on a 3.0 T Siemens Trio Tim scanner in the Brain Imaging Center at South China Normal University. We adopted the coronal slice orientation scanning for the functional imaging runs to minimize signal loss and distortion in temporal lobe regions due to the magnetic susceptibility artifact (Axelrod & Yovel, 2013). Specifically, the functional images were acquired with a T2*-weighted gradient echo-planar imaging (EPI) pulse sequence (TR = 2,000 ms, TE = 30 ms, flip angle = 90°, 37 slices, FOV = 224 mm × 224 mm, inplane resolution = 3.5×3.5 , slice thickness = 3.5 mm with 0.7 mm gap). T1-weighted high-resolution structural images were acquired between two tasks for each participant. Specifically, these images were acquired with a magnetization-prepared rapid acquisition gradient echo (MP-RAGE) sequence and sagittal slice orientation (176 slices, TR = 1,900 ms, TE = 2.53 ms, FOV = 256 mm × 256 mm, flip angle = 9°, voxel size = $1 \times 1 \times 1$ mm³, duration = 4 min 26 s).

We used SPM12 (Wellcome Department of Imaging Neuroscience, London, UK; www.fil.ion.ucl.ac.uk/spm/) for MRI data preprocessing and univariate analyses. All functional images were corrected for head-motion and realigned to the first functional image for each participant. The mean functional images were coregistered with the structural image and then segmented for each participant. The realigned functional images were smoothed with a Gaussian kernel of 6-mm full width at half maximum. The resulting smoothed functional images were used for the univariate analysis. The unsmoothed native-space functional images were used for the partial RSA.

2.6 | Representation similarity analysis

We used the CoSMo RSA toolbox (Oosterhof, Connolly, & Haxby, 2016) and customized Matlab functions for this analysis. Specifically, we conducted partial RSA on native and unsmoothed functional images. We first used the general linear model (GLM) with an interest regressor for each experimental phrase, one no-interest regressor for the filler phrases, and six no-interest regressors for the motion realignment parameters. We used the true trial duration of phrases (2.2 s) in the GLM model. High-pass filtering was used with a time constant of 128 s to reduce the influence of low-frequency noise. The 120 t-statistic maps of the experimental phrases were further generated in each task. We then defined a spherical searchlight (about 100 voxels) for each voxel with its nearest neighbor voxels. The t-statistic values of each spherical searchlight were normalized and further extracted to calculate distances between each pair of phrases (using 1 – Pearson correlation). This created the RDMs based on neural activation patterns (Figure 3).

In the partial RSA, partial Spearman's rank correlation was calculated to assess the association between the neural RDMs and the target

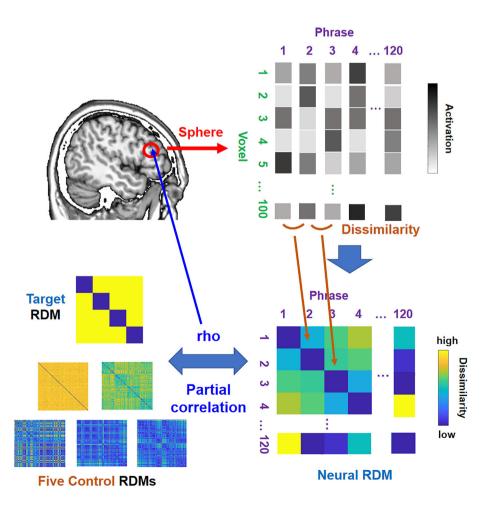


FIGURE 3 The illustration of partial RSA in the present study. In each sphere searchlight, the *t*-statistic values of 100 voxels for each phrase were first extracted. These values were used to calculate the dissimilarity between the members of each pair of phrases, which created the neural pattern RDM. The correlation between the neural pattern RDM and the target RDM was calculated, while control RDMs. The resulting partial Spearman's rank correlation (rho) was finally mapped back to the central voxel of each sphere searchlight

composition relation RDM while controlling for the variances of all other control RDMs (Feng, Gan, Wang, Wong, & Chandrasekaran, 2017; Xu et al., 2018). The resulting similarity values were mapped onto the central voxel of each sphere searchlight. The center of the searchlight volume was moved one voxel at a time within the gray matter of the brain. The similarity values of all voxels were *r*-to-*z* transformed using the *atanh*' algorithm. The similarity map of each participant was normalized to the Montreal Neurological Institute (MNI) template space and spatially smoothed with a Gaussian kernel of 4-mm full width at half maximum (FWHM). We combined the maps across participants and used onesample *t*-tests to examine significant brain regions in each task. The results were corrected for multiple comparisons using voxels significant at 0.001, with an FWE correction at the cluster level of 0.05. The BrainNet View toolbox was used to show the significant activations as *t*value maps on MNI brain surface template (Xia, Wang, & He, 2013).

2.7 | Univariate analyses

We used GLM for the first-level univariate analyses. We included the regressors of interest for experimental phrases, seven no-interest regressors for filler phrases, and motion realignment parameters. High-pass filtering was used with a time constant of 128 s as in the partial RSA. Voxel-wise parameter estimates for the interest regressors were estimated and used to generate statistical maps of responses to experimental phrases versus baseline responses in each task.

For the group-level analyses, the contrast images were first normalized onto the MNI space using the parameters obtained in the segmentation step. The normalized contrast maps were then combined across participants. One-sample *t*-tests were used to examine the significant activations and deactivations of experimental phrases > baseline in each task. Paired sample *t*-tests were used to examine brain regions where there was a significant task effect on activation. We used the same correction threshold for multiple comparisons as in the RSA (voxel: p < .001, cluster: FWE, p < .05).

3 | RESULTS

3.1 | Behavioral results

The ACC and RT of the separate behavioral experiment were shown in Table 2 and Figure 4. We first used repeated-measures ANOVA to examine the difference in ACC and RT across the four types of -WILEY <u>2211</u>

composition relations in each task. In the CRP task, the ANOVA results showed a significant main effect of composition relations in ACC, F (3, 45) = 5.22, p < .05. Further comparisons showed that the ACC for the coordinated predicates was significantly higher than the ACC for the subject-predicate and modifier-noun phrases (ps < .01). The ANOVA showed a significant main effect of composition relations in RT, F (3, 45) = 16.50, p < .001. Further comparisons showed that the RT for the verb-object and coordinated predicates was significantly shorter than the RT for the subject-predicate and modifiernoun phrases (ps < .005). In the WP task, no significant difference of composition relations was found in either the ACC, Fs (3, 45) < 1, or RT, Fs (3, 45) < 1.98, p = .13. In addition, we also carried out paired sample t-tests to examine the differences between the two tasks in the ACC and RT for all phrases (including filler phrases). The results showed that the CRP task had significantly lower ACC, t (15) = 4.01, p < .005, and longer RT, t (15) = 8.80, p < .001. These results suggest that the CRP task was more difficult for participants than the WP task.

3.2 | RSA results

As shown in Figure 5, the partial RSA searchlight results showed that in the CRP task, the composition relation RDM was significantly correlated with the activity pattern of a cluster around the left AG (39%) extending to the middle occipital cortex (34%) and inferior parietal lobe (IPL, 27%) (peak intensity: t = 4.63; peak MNI coordinates: x, y, z = -30, -67, 38; 334 voxels). In the WP task, there was no significant correlation between the composition relation RDM and the neural pattern in any brain area.

3.3 | Univariate analyses

As shown in Figure 6, the univariate searchlight analyses found significant positive activations in bilateral occipital areas in experimental phrases > baseline in both the CRP and WP tasks. Since our tasks involve visual processing, this result is consistent with previous findings showing the effects of visual processing in occipital areas (Chiarelli, Di Vacri, Romani, & Merla, 2013). Further, the contrast of experimental phrases > baseline also showed negative activation in partial left AG under both tasks. This is consistent with previous findings that AG is part of the default mode network (DMN; Seghier, 2013). More importantly, the paired sample *t*-test of CRP

TABLE 2The ACC and RT results ofthe separate behavioral experiment

	ACC		RT (ms)	
Composition relation	CRP	WP	CRP	WP
Argument saturation (subject-predicate)	0.90 (0.09)	0.99 (0.03)	1,591 (425)	893 (259)
Argument saturation (verb-object)	0.94 (0.03)	0.98 (0.02)	1,368 (275)	900 (244)
Modification (modifier-noun)	0.89 (0.11)	0.98 (0.02)	1,531 (345)	935 (268)
Modification (coordinated predicates)	0.97 (0.08)	0.98 (0.02)	1,295 (261)	894 (220)

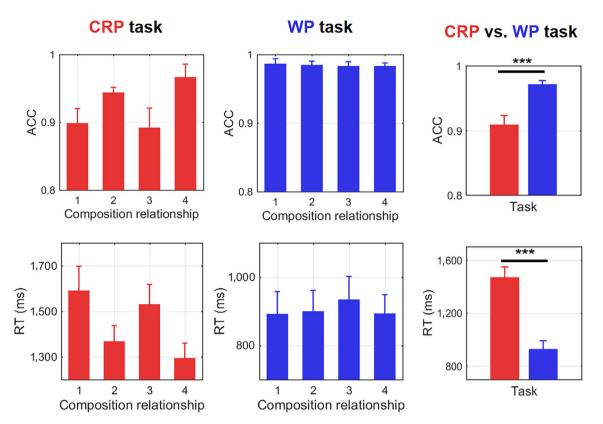
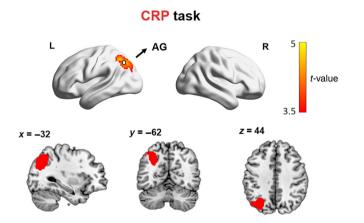


FIGURE 4 The ACC and RT results in the separate behavioral experiment. The upper graphs show the ACC for four composition relationships in each task and the ACC for all phrases in both tasks. The lower graphs show the corresponding results with the RT measure. The labels on the *x*-axis (1, 2, 3, and 4) denote the four composition relations for the experimental phrases, respectively: argument saturation (subject-predicate), argument saturation (verb-object), modification (modifier-noun), and modification (coordinated predicates). In all graphs, the red color denotes the 1-back CRP task, and the blue color denotes the 1-back WP task. Error bars denote the standard error of the mean. ACC, accuracy; RT, reaction time. CRP, composition relation probe; WP, word probe. *p < .05; **p < .01; ***p < .005



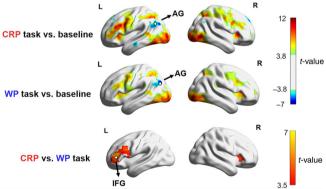


FIGURE 5 Whole-brain searchlight partial RSA results in the 1-back CRP task. The illustrations at top show significant brain regions projected onto the surface brain template. The illustrations at bottom show significant (binary) brain regions projected onto the anatomic brain template from three views: sagittal, coronal and axis. AG, angular gyrus; CRP, composition relation probe; L, left hemisphere; R, right hemisphere

FIGURE 6 The results of whole-brain univariate analyses. The brain regions with significant activation are projected onto the surface brain template. The upper and middle illustrations show significant activations (both positive and negative) in the contrast of experimental phrases > baseline in each task. The lower illustrations show results of the task effect (CRP task vs. WP task). CRP, composition relation probe; WP, word probe; IFG, inferior frontal gyrus; L, left hemisphere; R, right hemisphere

task versus WP task showed greater activations in the left IFG (84%) extending to the middle frontal gyrus (MFG, 16%) (peak intensity: t = 6.17; peak MNI coordinates: *x*, *y*, *z* = -42, 41, 11; 223 voxels) and

in the right IFG (46%) extending to insula (33%) and putamen (21%; peak intensity: t = 4.24; peak MNI coordinates: *x*, *y*, *z* = 33, 26, -1; 37 voxels). No significant activation was found in the paired sample *t*-

test of the WP task versus CRP task. In addition to the main analysis presented here, we also performed an additional ROI-based univariate analysis (Supporting Information Section S1), which revealed similar effects as reported here.

4 | DISCUSSION

The present study examined the neural representation of linguistic composition, using Mandarin Chinese as the case study. The partial RSA searchlight results showed that the composition relationship RDM was significantly correlated with the activity patterns around the left AG in the CRP task. However, no significant correlations were found in the WP task. These results highlight the role of left AG in representing linguistic composition relations. This conclusion, although in line with previous results that showed composition effects in left AG, seems to also deviate from previous work that identified a larger network, including the left AG, IFG, and LATL, as the neural basis for linguistic composition. A significant methodological difference between the current study and previous ones is that we took advantage of multivariate RSA, whereas the previous studies used the more traditional univariate analysis. Traditional univariate analyses use overall activation intensity to quantify fMRI data, whereas RSA uses fine-grained activation patterns. Traditional univariate analyses draw conclusions by making contrast comparisons between conditions, and RSA draws evidence from the correlation between the dissimilarity matrix of the stimuli and the neural activities in the brain. These two analyses therefore may provide complementary information on the neural mechanisms underpinning language processing. In addition to the RSA, we also performed an additional univariate analysis, and found greater activations in the bilateral IFG areas in the CRP task relative to the WP task. We discuss the theoretical and methodological implications of these findings below.

4.1 | The sensitivity of left AG in distinguishing fine-grained composition relations

As mentioned in the introduction, in previous work that investigates the brain regions responsible for linguistic composition, the most common paradigm was to compare a condition with a single type of composition relation with another baseline condition that involves no composition. This paradigm can identify brain areas that broadly speaking are involved in linguistic composition, but it did not address whether and how different types of composition relations could be represented in the brain. To capture the brain responses elicited by different types of composition relations, one also needs to tease apart any effect from the surface linguistic forms that co-vary with the changes in the composition relation. This could be difficult for a language like English. In the present study, Mandarin Chinese allowed us to design stimuli that vary in their composition relations but maintain a relatively uniform surface form. We also used partial RSA to examine the brain regions that are sensitive to different types of

composition relations while controlling for the effects of other variables such as semantic and visual similarity. Partial RSA is well suited to capture brain responses reflecting (dis)similarities between stimuli, allowing us to more precisely identify brain regions that target the details of representational content. This approach has been used in previous studies across multiple empirical domains (Feng et al., 2017; Wurm & Caramazza, 2019). In the present study, we used multiple RDMs to isolate the effects of information content that co-exists in the experimental stimuli, such as composition relationship, semantic similarity, visual similarity, and so forth. Subsequently, we examined the correlations between the neural RDMs and the composition relation RDM while controlling for the RDMs of other variables. In the more conventional univariate analysis, it is more common to control for confounding variables by setting up control comparison conditions in the experimental design. But for natural language stimuli, it could be challenging to set up ideal control conditions that completely distinguish the target effect from other effects (Pylkkänen, 2019).

The RSA found a significant cluster around left AG extending to the middle occipital cortex and IPL. The significant effect in left IPL is consistent with previous findings that showed this area is sensitive to relationality (Williams, Reddigari, & Pylkkänen, 2017). The significant effect in left AG area is of critical interest to us since this area was already implicated in previous studies as one important region for composition, and with the help of the RSA, our findings further suggest that left AG may be unique in its ability to represent and distinguish fine-grained information of different types of composition relations. To provide more corroborating evidence for the role of left AG, we also performed three additional analyses. The details of these additional analyses are presented in the Supporting Information Sections S3-S5. First, as mentioned in Section 2.3, for the current RSA. the target composition RDM is a categorical RDM based on four different composition relations, each corresponding to a type of phrase construction in Table 2. These four different relations could be classified into two general categories, based on which we constructed a number of gradient composition RDMs as the target RDM. The new partial RSA using these gradient composition RDMs showed highly consistent results with the current RSA (Figure S3). Second, apart from the whole-brain searchlight RSA, we also conducted an ROIbased RSA, in which we defined an anatomic ROI for the left AG region (AAL altas). As shown in the Supporting Information Section S4, this analysis also found significant correlations between the composition RDMs and the left AG in the CRP task but not in the WP task. Finally, if left AG is responsible for representing fine-grained composition relations, we should expect the activities in this region to correlate with the computational cost of constructing composition relations at the individual item level. To test this, we constructed an RDM that reflects the strength of association between the two words that formed the experimental phrases, with the assumption that the stronger the association between the two words, the easier people can semantically compose them together (Price, Bonner, Peelle, & Grossman, 2015). As shown in the Supporting Information Section S5, this analysis found a significant correlation between the association strength RDM and a number of brain regions, and most important for

the current purpose, left AG is included in these regions that showed a significant correlation. Taken together, different analyses consistently revealed left AG as a key region that is sensitive to the finegrained composition relation in the linguistic input. The fact that both the gradient RDMs and the association strength RDM significantly correlate with the activity patterns in left AG provides strong evidence that this region does not simply "combine" elements together, it is highly sensitive to the specific relations and semantic features that are involved in the composition.

The current finding therefore makes an important contribution to the body of work that discusses the role of left AG in language comprehension, many of which have converged on the effect of composition in left AG. Increased activity in left AG has been found in sentences versus unstructured lists (Fedorenko et al., 2012; Matchin et al., 2017), and it has been argued that left AG belongs to a larger combinatory network (Pylkkänen, 2019). Previous studies that looked at the involvement of left AG in the composition at the phrasal level are particularly relevant for the current study. For instance, Bemis and Pylkkänen (2012) examined composition in simple adjective-noun phrases in both visual and auditory modalities. The MEG results localized the neural basis for composition to left AG and LATL. Price et al. (2015) also compared meaningful adjective-noun combinations (e.g., loud car) and "nonmeaningful" baseline (e.g., moss pony). The results showed that the process of combining concepts to form meaningful representations specifically modulates neural activity in left AG. which suggested a critical role for the left AG in conceptual combination. The causal relation between the mechanism of semantic integration and left AG was further supported by transcranial direct current stimulation (tDCS; Price, Peelle, Bonner, Grossman, æ Hamilton, 2016). Several previous studies documented the involvement of left AG in supporting relations between verbs and their arguments or modifiers (Meltzer-Asscher, Schuchard, Ouden, & Thompson, 2013; Thompson et al., 2007; Thompson, Borna, & Fix, 2010). For instance, Thompson et al. (2007) found more activation in the left AG for verbs that combine with more arguments (buy) than for verbs that combine with fewer arguments (sit). Boylan, Trueswell, and Thompson-Schill (2015) found that two phrases that share the same verb (e.g., eats meat, eats quickly) elicited similar activity patterns in the left AG, but two phrases that share the same noun did not (eats meat, with meat). In an fMRI study, Matchin, Liao, Gaston, and Lau (2019) compared lexically matched noun phrases (NP, the frightened boy) and verb phrases (VP, frightened the boy), as well as the unstructured word lists. The VP and NP phrases elicited a larger left AG response than unstructured word lists, but no activation difference was found in left AG between the VP and NP conditions. Matchin et al. (2019) concluded that the left AG is involved in processing event information expressed by a linguistic expression (e.g., frightened) independent from its syntactic categories. Taken together, previous studies investigating a variety of constructions have converged to reveal the role of AG in linguistic composition. Building upon this investigation, the current results make a further contribution by demonstrating that the composition relation is not just represented in an all-or-nothing fashion in left AG; instead, this

region is sensitive to the fine-grained differences between different types of composition relations.

4.2 | The effects of tasks

In the current study, the RSA found a significant correlation between the neural RDM and composition relation RDM in the CRP task but not the WP task, despite the fact that the two tasks share identical experimental stimuli. In the CRP task participants were explicitly instructed to reflect on the ways two words are combined, whereas in the WP task participants were instructed to pay attention to only the similarity between words. One potential concern is that the results we observed, instead of a reflection of the composition effect, actually reflect some strategic effects associated with performing the 1-back CRP task. For example, on each trial in the CRP task, instead of composing words together, a participant may have simply maintained the form of each phrase in memory (e.g., a "adjective + adjective" phrase or a "verb + noun" phrase), and used that knowledge to perform the task. We acknowledge that the CRP task is not a naturalistic comprehension task, and future work should examine natural comprehension context. But we think a task-strategy interpretation of the current results is unlikely considering the convergence of different analyses reported earlier. Both the partial RSA and the ROI-based RSA revealed significant effects in left AG, regardless of whether the composition RDM is constructed in a categorical or gradient manner. The task-strategy-only interpretation would not expect to make graded distinctions between different types of composition relations. Related to this, the effect of the association strength RDM is also unexpected if the CRP task did not probe the actual composition relation between words.

It may also seem surprising at first glance that the WP task revealed no effect of composition in the AG area, given the large body or previous work that demonstrates successful semantic composition and semantic comprehension in general in the absence of any explicit tasks (Altmann & Kamide, 1999; Altmann & Kamide, 2009; Scott et al., 2000). After all, successful language comprehension in daily communication does not depend on explicit tasks that draw people's attention to compositional relations. We would argue, however, that the WP task is substantially different from the passive tasks used in previous studies. In a standard passive task, for example, when participants were simply listening to some linguistic input without performing any specific tasks (Evans et al., 2014; Scott et al., 2000), participants could be naturally engaged in language comprehension without being distracted by any other secondary tasks. In the WP task, participants were required to focus on each word of the phrase, because they need to match the word in two consecutive trials. This task could therefore distract participants from the regular language comprehension process, effectively rendering the 2-word phrase as a 2-word list. In other words, the WP task may inhibit active engagement with the regular combinatorial processing for linguistic stimuli. Although there is some evidence from priming that suggests semantic integration between two words is not under heavy strategic control

(Estes & Jones, 2009), the conclusion is drawn based on an experimental design and paradigm that is very different from the current study. More directly relevant to the current study, Graves, Binder, Desai, Conant, and Seidenberg (2010) also found task effect on linguistic comprehension. This study used meaningful phrases (e.g., lake house) and unfamiliar phrases with minimal meaning (house lake) as stimuli and manipulated two tasks. In the classification task, participants were asked to judge whether the phrase was meaningful. In the 1-back WP task, they were asked to judge whether either word in the current phrase matched a word in the previous phrase. The fMRI results showed significant differences between tasks, and the authors argued that the classification task engaged brain areas related to combinatorial processing (including right angular gyrus, dorsomedial prefrontal cortex, and bilateral posterior cingulate/precuneus), whereas the 1-back WP task primarily engaged the lexical processing in the brain.

Another potential concern with our tasks is that the CRP task is more difficult than the WP task, as shown by the RT and accuracy results from the behavioral experiments, and the AG effect in the CRP task may reflect task difficulty instead of linguistic composition. More generally, there may be different degrees of difficulty associated with each individual stimulus item, and AG could be sensitive to that. This possibility can be ruled out by the RT RDM we constructed. Assuming that RTs in the behavioral task is a good index of item-level difficulty, the RT RDM controls for processing difficulty that may vary between items and tasks. We included more details for the RT RDM results in the Supporting Information Section S2. The RT RDM itself significantly correlated with neural pattern around multiple brain areas such as right IFG in the CRP task, but the neural pattern around left AG was not significantly correlated with the RT RDM. Moreover, using the RT RDM as a control RDM, the target composition RDM still showed a significant correlation with the AG area. Taken together, these results suggest that the AG effect observed in the RSA is not driven by the processing difficulty associated with different items/ tasks. It is not to say that the AG area is never sensitive to processing difficulty. It has been suggested that left AG could be involved in general cognitive processing (Seghier, 2013), and previous studies also revealed that AG can serve noncommunicative functions as well (Geranmayeh et al., 2012; Humphreys & Lambon Ralph, 2015). Consistent with this, our univariate analyses showed deactivation of partial left AG in experimental phrases > baseline in both the CRP and WP tasks (Figure 6), which provided evidence that AG is part of the default mode network (DMN, Seghier, 2013). In general, left AG may contain multiple sub-regions and could serve multiple different purposes, and combinatorial processing is just one of them.

4.3 | Linguistic composition beyond left AG

It is interesting to observe that the conventional univariate analysis revealed greater activations in bilateral IFG during the CRP task relative to the WP task, even though the IFG did not emerge as a relevant brain region in the RSA. This is different from some previous studies that found IFG effects in composition. For instance, Zaccarella and

Friederici (2015) argued that the left pars opercularis in IFG were involved in the basic composition process. The primary comparison in their study was between a syntactic phrase context, such as this flirk, and a word list context, such as apple flirk, and a univariate analysis found greater activation in left IFG for the former condition. We see two possibilities to explain this discrepancy. First, since RSA is primarily sensitive to the representational content of the stimuli (Mur, Bandettini, & Kriegeskorte, 2009), it is possible that what RSA revealed in AG reflects a more fine-grained representation of different types of composition relations: whereas the IFG, on the other hand, could be instantiating a more coarse-level composition function. Another possibility is that the IFG region is not responsible for linguistic composition per se, but it may contribute to some general cognitive functions, such as working memory, cognitive control, and attention allocation, which support the linguistic composition task (Petersen & Posner, 2012). There is a long-standing debate in the literature regarding the role of IFG in language comprehension. Most relevant for the current purpose, the central question is whether IFG contributes to some specific aspect of linguistic structure building, and thereby is responsible for composition by extension, or it contributes to some general cognitive mechanisms that language comprehension relies on (Hagoort, 2014; Rogalsky & Hickok, 2011). Among the latter class of proposals, IFG activation could reflect the role of working memory (Badre & Wagner, 2007), inhibition function (Aron, Robbins, & Poldrack, 2004), and conflict management (Silvetti, Alexander, Verguts, & Brown, 2014). The behavioral results in the current study showed lower accuracy and longer RT in the CRP task relative to the WP task, suggesting that the CRP task is more cognitively demanding for the participants. The greater activation in the IFG area for the CRP task relative to the WP task in the univariate analysis (also see the ROI-based univariate analyses in the Supporting Information Section S1) could, at least in part, reflect the greater cognitive resources devoted to support the process of computing composition relations. We also note that, however, the hypothesis that IFG activities reflect greater demands on resources needs to be further tested in future work. In the RSA, we did not find a correlation between the RT RDM and the neural RDM in the left IFG (Supporting Information Section S2), raising questions about the exact relationship between the left IFG and task demands.

The present results did not reveal any composition computation or task effect in LATL, although this region has been reported in previous MEG studies as being responsible for composition processing (Pylkkänen, 2019; Zhang & Pylkkänen, 2018). The discrepancies could be due to a number of methodological differences. In terms of experimental design, the present study looked for the brain regions that could discriminate four different types of composition relations at the phrasal level. All target phrases were semantically plausible and syntactically well formed. In contrast, previous work compared syntactically well-formed phrases with word lists. In terms of data analysis, the RSA examined the systematic variance distributed across voxels and the activation intensity was demeaned across phrases (Coutanche, 2013). Previous studies used univariate analysis, which quantifies local average activation intensity across voxels between 2216 WILEY

conditions (Kriegeskorte, Goebel, & Bandettini, 2006). Apart from these differences, one limitation of the current study is that with fMRI recording, the temporal lobes are subject to distortion and signal loss due to the magnetic susceptibility artifact in fMRI (Olman, Davachi, & Inati, 2009), although we adopted coronal slice orientation scanning to minimize this influence (Axelrod & Yovel, 2013). Previous MEG studies did not face this problem. More studies are needed to clearly address the role of LATL.

5 | CONCLUSION

The present study makes a novel contribution by applying multivariate partial RSA to study the neural mechanism of linguistic composition. Our study also broadens the existing empirical coverage by studying composition in Mandarin Chinese. Our findings highlight the role of left AG in representing and distinguishing fine-grained linguistic composition relations.

CONFLICT OF INTEREST

The authors have declared no conflicts of interest for this article.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Wenjia Zhang b https://orcid.org/0000-0001-8328-6128 Suiping Wang b https://orcid.org/0000-0001-8726-169X

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