# Worlds shaped by words: a cross-linguistic investigation into the neural mechanisms of lexico-syntactic feature production

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# CHAPTER 2

# Processing Mandarin Chinese classifiers as a lexico-syntactic feature during noun phrase production

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**Abstract:** During speech production, lexico-syntactic features associated with nouns (e.g., grammatical gender, classifiers, number) are assumed to be automatically activated. Although previous studies have provided evidence for this assumption by examining *classifier congruency effects*, empirical validation of this mechanism in Mandarin Chinese remains limited. The present study investigated whether a *classifier congruency effect* can be reliably elicited during noun phrase production in Mandarin and explored how this effect relates to semantic processing. We employed a picture-word interference (PWI) paradigm, incorporating several methodological refinements. Both classifier congruency and semantic relatedness between the target and distractor words were manipulated. Behavioural results replicated the *semantic interference effect*, with longer naming latencies observed for semantically related distractors than semantically unrelated ones. Although no main effect of classifier congruency was found, a significant interaction with semantic relatedness emerged. Classifier incongruency led to delayed naming under semantically related conditions. ERP results further revealed that both the *semantic interference* and *classifier congruency effects* peaked within the N400 time window, with the *semantic interference effect* emerging slightly earlier. These findings provide further evidence that classifier information is automatically activated as a lexico-syntactic feature during lemma access, and that this activation is influenced by semantic processing. The present results contribute both conceptually and methodologically to advancing our understanding of classifier processing in Mandarin Chinese.

**Keywords:** picture naming, picture-word interference, lexico-syntactic feature, classifier

## 2.1. Introduction

While natural speech unfolds linearly in time, the underlying structure of language is hierarchical. In many languages, content words in a sentence constrain the selection and morphological form of function words. For example, in German, all nouns are categorised into three grammatical genders (masculine, feminine and neuter). The grammatical gender of a noun specifies the form of preceding determiners. In the phrase "*das Wasser*" (the water), the neuter noun "*Wasser*" requires the neuter determiner "*das*", rather than the masculine "*der*" or the feminine "*die*". A comparable system exists in Mandarin Chinese, wherein nouns are required to be paired with classifiers in a manner that is both syntactically and semantically constrained. In the noun phrase "*yì běn zázhì*" (one + classifier + magazine), the classifier "*běn*" must be used for book-like objects. Grammatical gender in Indo-European languages and classifiers in Mandarin Chinese constitute lexico-syntactic features hypothesised to be stored in the mental lexicon alongside lemmas (Levelt et al., 1999a). While extensive research has examined the processing of grammatical gender in Indo-European languages (for a review, see Wang & Schiller, 2019), the mechanisms underlying classifier processing in Mandarin Chinese remain notably limited. The present study builds on prior research by adopting well-established paradigms and introducing novel experimental materials and analytical methods to examine the cognitive processing of classifiers in Mandarin Chinese.

### 2.1.1. Retrieval of lexico-syntactic features during noun phrase production

Major language production models propose that speech involves three stages: the conceptualisation stage, the formulation stage, and the articulation stage (e.g., Bock & Levelt, 1994; Caramazza, 1997; Dell, 1986, 1988; Garrett, 1975, 1980; Levelt, 1989, 1992, 1999; Levelt et al., 1999b; Oppenheim et al., 2010; Roelofs, 1997, 2000; Roelofs & Ferreira, 2019; for an overview, see Griffin & Ferreira, 2006). The *WEAVER++ model* (Levelt et al., 1999a) proposes that lexico-syntactic features are activated at the lemma stratum — an intermediate layer between the conceptual and word-form strata. During picture naming, activation spreads from the concept to the associated lemma and subsequently to the connected lexico-syntactic features (e.g., grammatical gender, number, or classifier). If these features are overtly produced, activation further spreads to their word form, enabling retrieval of appropriate determiners or classifiers. In contrast, Caramazza's (1997) *Independent Network Model* suggests three distinct networks — lexical-semantic, syntactic, and phonological networks. In this model, the lexical-semantic network can activate the syntactic and phonological networks independently. The model argues for parallel activation of syntactic and phonological networks directly from semantics, positing that lexico-syntactic feature processing may be bypassed if not phonologically instantiated (e.g., when German nouns of different grammatical genders exhibit identical determiners in the plural form).

### 2.1.2. Gender congruency effect

Research into the processing mechanisms of lexico-syntactic features has initially concentrated on grammatical gender. Schriefers (1993) investigated the processing of grammatical gender using the *picture-word interference* (PWI) paradigm in Dutch. In this experimental paradigm, a distractor word is superimposed onto a target picture. Participants are required to name the target pictures verbally while disregarding the distractor words. A *gender congruency effect* was observed, whereby naming latencies increased when the target and distractor nouns differed in grammatical gender. This finding suggests that the grammatical gender information of distractors is automatically activated during the process of lemma retrieval, thereby competing with the grammatical gender nodes of the target nouns for selection. Schiller and Caramazza (2003) challenged this interpretation (i.e., *gender selection interference hypothesis*, GSIH), proposing a *determiner selection interference hypothesis* (DSIH): the observed effect arises not from grammatical gender activation per se but from competition between determiners. They found that the *gender congruency effect* diminished when the determiners of both the target and distractor stimuli were congruent, even in the presence of grammatical gender incongruency. Hence, they refer to this phenomenon as the *determiner congruency effect*. Although behavioural studies yield mixed interpretations, electrophysiological evidence supports the activation of grammatical gender during noun phrase production. Bürki et al. (2016) observed differences in ERP signals around 210 ms before articulation onset between gender-congruent and gender-incongruent conditions (*mean RT* = 798 ms). Together, these results suggest that grammatical gender information may be automatically activated and selected as a lexico-syntactic feature during noun phrase production.

### 2.1.3. Classifier congruency effect

The investigation of lexico-syntactic feature processing has also gained traction in research on Mandarin Chinese. Although Mandarin lacks rich morphological inflections and displays more flexible syntax, it features a classifier system similar in function to grammatical gender (Adams & Faires Conklin, 1973; Allan, 1977; Contini-Morava & Kilarski, 2013; Kilarski, 2013). Several studies have used the PWI paradigm to explore whether classifiers are activated during noun phrase production in a manner analogous to grammatical gender (Huang & Schiller, 2021; Li et al., 2006; Zhang & Liu, 2009). These studies revealed that naming latencies increased when the classifiers of the distractor and target noun were incongruent, demonstrating a *classifier congruency effect*. This suggests that classifier information is automatically activated during lemma access. Unlike grammatical gender processing, which typically occurs in the P600 window (e.g., Foucart & Frenck-Mestre, 2011; Gunter et al., 2000; Hagoort & Brown, 1999), the *classifier congruency effect* is often reflected in N400-like ERP responses (Huang & Schiller, 2021; Wang et al., 2019). The N400 component is generally associated with semantic processing (for a review, see Kutas & Federmeier 2011), suggesting that classifier activation may be more semantically influenced than grammatical gender. In the study by Huang and Schiller (2021), both the congruency of the classifiers and the semantic relatedness between the target and distractor nouns were manipulated. The experiment also revealed a *semantic interference effect* (for a review, see Bürki et al., 2020), wherein naming latencies were longer when the distractor and the target noun belonged to the same semantic category, compared to semantically unrelated conditions. This behavioural effect was mirrored in the ERP data as an N400 component. Mandarin classifiers are largely semantically driven, categorising nouns based on inherent semantic features. For instance, the classifier "*tái*" is typically used for machines, whereas "*liàng*" is used for vehicles. The findings reported by Huang and Schiller (2021) that both the *classifier congruency effect* and the *semantic interference effect* elicited similar ERP components, particularly within the N400 time window, suggest that classifier processing may be closely tied to the processing of semantic category information. Nevertheless, the precise nature of this relationship remains underexplored in the literature.

Although several studies have reported evidence for a *classifier congruency effect* in Mandarin and have suggested that classifier information is automatically activated and selected during noun phrase production, these findings so far come from a relatively small number of investigations (Huang & Schiller, 2021; Li et al., 2006; Wang et al., 2019; Wang & Schiller, submitted; Zhang & Liu, 2009). Furthermore, some aspects of the experimental design and data analysis in these studies leave room for improvement. One issue concerns the use of the general classifier "*gè*", which was included in the stimulus materials of some previous experiments. As a result of its extensive grammaticalization, "*gè*" has lost much of its original semantic content and is widely used with nearly all nouns in spoken Mandarin (Myers, 2000). This presents two potential problems: first, the processing of "*gè*" may rely primarily on syntactic routines, which distinguishes it from more semantically specific classifiers (Frankowsky et al., 2022; Qian & Garnsey, 2016). Second, stimuli in the classifier-incongruent condition may not have been truly incongruent, given "*gè*'s" broad compatibility.

Another limitation relates to the analytical methods employed. Most prior studies used traditional average-based analyses, which are limited in their capacity to account for variation across participants and items or to handle unbalanced datasets. In comparison, (generalised) linear mixed-effects models (GLMMs/LMMs) have a better handle on missing data, larger statistical power, better control of the type I errors and allow for generalisation across items (Baayen et al., 2017; Barr, 2013; Frömer et al., 2018; Matuschek et al., 2017).

Finally, time windows and regions of interest (ROIs) in prior studies are typically chosen based on prior assumptions or findings. While this approach is widely used, it carries the risk of overlooking subtle effects that may occur in adjacent time windows or spatial areas. In contrast, a data-driven approach using permutation tests across all epochs may provide a clearer and more objective understanding of when and where effects emerge (Voeten, 2023a, 2023b).

Taken together, while the *classifier congruency effect* has been reported in Mandarin, the limited number of studies and methodological considerations suggest that further investigation is warranted. The present study seeks to contribute to this line of research by employing refined experimental materials and more detailed analytical methods to explore whether the *classifier congruency effect* can be reliably observed during noun phrase production in native Mandarin speakers.

### 2.1.4. The current study

The present study aims to replicate and extend the findings of Huang and Schiller (2021) by implementing three critical methodological updates. First, the experimental materials were revised to exclude the general classifier "*gè*", ensuring a one-to-one pairing of classifiers and nouns. Second, we adopted a permutation-based approach to identify time windows in the EEG analysis, allowing for data-driven determination of time windows and electrodes. Third, we used (generalised) linear mixed-effects models (GLMMs/LMMs) at the single-trial level.

The experiment manipulated semantic relatedness and classifier congruency between target and distractor nouns using a PWI paradigm. We expect to observe both *semantic interference* and *classifier congruency effects* based on previous findings (Huang & Schiller, 2021; Wang & Schiller, submitted). Specifically, we predicted that semantically related distractors would lead to longer naming latencies than unrelated ones and that naming would be slower in classifier-incongruent conditions than classifier-congruent conditions. In the EEG data, we expect a more negative-going ERP component in the N400 time window for semantically unrelated distractors relative to related ones. Meanwhile, we expect classifier-incongruent trials to elicit more negative voltage amplitudes than classifier-congruent trials.

## 2.2. Methods

### 2.2.1. Participants

Thirty-five native Mandarin Chinese speakers (eight males and twenty-seven females) were recruited from the University of Münster in Germany. The average age of the participants was 26.33 years (SD = 3.28), and six of them were left-handed. All participants reported having normal or corrected-to-normal vision, with no history of neurological, psychological, or language impairments. Informed consent was obtained prior to the experiment, and participants were provided with a debriefing form after completing the experiment, in accordance with the Ethics Code for Linguistic Research at the Faculty of Humanities, Leiden University (The Netherlands). Participants received monetary compensation for their participation. Five participants were excluded due to insufficient valid data.

### 2.2.2. Materials

Twenty-five black-and-white line drawings representing objects used in daily life were selected from Liu's picture database (Liu et al., 2011) and used as target pictures in the picture naming task. The names of these pictures correspond to monosyllabic (36%) or disyllabic (64%) words in Mandarin Chinese. Each target picture was assigned four distractors. The distractors were paired with target words depending on whether they shared the same classifier as the target word or whether they belonged to the same semantic category as the target word, resulting in four experimental conditions (see Table 2.1), i.e., classifier-congruent and semantically-related (C+S+) condition, classifier-incongruent and semantically-related (C-S+) condition, classifier-congruent and semantically-unrelated (C+S-) condition, classifier-incongruent and semantically-unrelated (C-S-) condition.

**Table 2.1**

Examples of distractors presented with the target noun "猴子 (*monkey*, classifier 只 zhi)" in all conditions.

| | **Semantically related (S+)** | **Semantically unrelated (S-)** |
|---|---|---|
| **Classifier congruent (C+)** | 熊猫 (*panda*, 只 zhi) | 袜子 (*socks*, 只 zhi) |
| **Classifier incongruent (C-)** | 马 (*horse*, 匹 pi) | 门票 (*ticket*, 张 zhang) |

The semantic relatedness of each pair of distractor and target words was assessed by fifteen native Chinese speakers who did not participate in the naming task. Ratings were made on a 7-point Likert scale, with higher scores indicating a stronger perception that the two words belong to the same semantic category. Statistical analysis of rating scores was conducted using the *clmm()* function from the "*ordinal*" package (Christensen, 2023) in RStudio Version 2024.04.2+764 (R Core Team, 2023). Fixed factors included classifier congruency and semantic relatedness, modelled using mixed-effects ordinal regression. Model selection followed a backward elimination procedure starting with the maximal random-effects structure. The final best-fitting model and its parameters are detailed in Table 2.A.1 of Appendix 2.A. The results demonstrated that there was a significant difference in rating scores between the semantically related ($M$ = 6.36, $SD$ = 1.04) and semantically unrelated ($M$ = 1.60, $SD$ = 1.12) conditions ($\beta$ = 3.831, $SE$ = 0.359, $z$ = 10.666, *95% CI* [3.127, 4.535], $p <$ 0.001), whereas there was no significant difference between the classifier-congruent condition ($M$ = 4.07, $SD$ = 2.59) and the classifier-incongruent ($M$ = 3.92, $SD$ = 2.64) condition ($\beta$ = 0.070, $SE$ = 0.059, $z$ = 1.180, *95% CI* [-0.046, 0.185], $p$ = 0.238).

To control for potential confounds, several lexical and visual features of the distractors were matched across conditions. Results of *Kruskal-Wallis tests* indicated that distractors across the four conditions did not show significant differences in word frequency ($H$(3) = 1.252, $p$ = 0.741, *95% CI* [6392.644, 10595.580]), visual complexity determined by the number of strokes ($H$(3) = 1.526, $p$ = 0.676, *95% CI* [12.456, 14.472]), number of syllables ($H$(3) = 2.095, $p$ = 0.553, *95% CI* [1.631, 1.809]) and phrase frequency of noun-classifier collocations ($H$(3) = 7.834, $p$ = 0.050, *95% CI* [1290.702, 2511.746]). The word frequency data were obtained from the Chinese Lexical Database (Sun et al., 2018). The phrase frequency data were retrieved and extracted from the BCC corpus (Xun et al., 2016), selecting only high-frequency noun-classifier collocations for experimental use. Last, distractors were not phonologically or orthographically related to the corresponding target nouns.

## 2.2.3. Design and procedure

This experiment followed a 2 × 2 within-subjects design, with classifier congruency (C) and semantic relatedness (S) as two fixed factors. Each of the four conditions (C+S+, C–S+, C+S–, C–S–) included 25 items. Participants were instructed to name all target pictures using noun phrases of the form "quantifier +

classifier + noun" during the picture naming task. Either two or three identical target pictures were randomly presented for each target to minimise potential confounds from repeatedly naming the same number. Consequently, each participant completed a total of 200 experimental trials. Eight additional trials were provided for warming up.

The presentation order of trials was pseudo-randomised using the Windows program Mix (Van Casteren & Davis, 2006) program, ensuring that trials with identical conditions, classifiers, or syllables were not presented consecutively. Trials with the same number of pictures could appear at most twice in a row. Additionally, the minimum distance between any two identical target words was ten trials. Also, the minimum distance between any two target words in the same semantic category was three trials. Each participant was presented with the stimuli in a different pseudo-random order.

The experiment was implemented in E-Prime 2.0 software (Psychology Software Tools, Pittsburgh, PA) and comprised three sessions: a familiarisation session, a practice session, and an experimental session. During the familiarisation session, all target pictures were presented sequentially on the screen for 3,000 ms, along with their corresponding names. Participants were instructed to indicate their familiarity with the pictures and target noun phrases by pressing a designated key. In the practice session, a string of letters ("XXXX") was superimposed on each target picture, and participants were instructed to ignore it while naming the picture using a noun phrase within 3,000 milliseconds. The experimenter provided corrections for any errors during this phase. The experimental session followed the same structure, except that distractor words replaced the letter strings (see Figure 2.1). Each trial began with a fixation cross ("+") displayed for 300 milliseconds, followed by a blank screen for 200 milliseconds. The target picture, along with the distractor, was then shown for 3,000 milliseconds, followed by a final blank screen for 500 milliseconds. Throughout the experiment, both EEG and vocal responses were recorded. In total, there were 200 trials distributed evenly across four blocks, with each block starting with two warm-up trials.

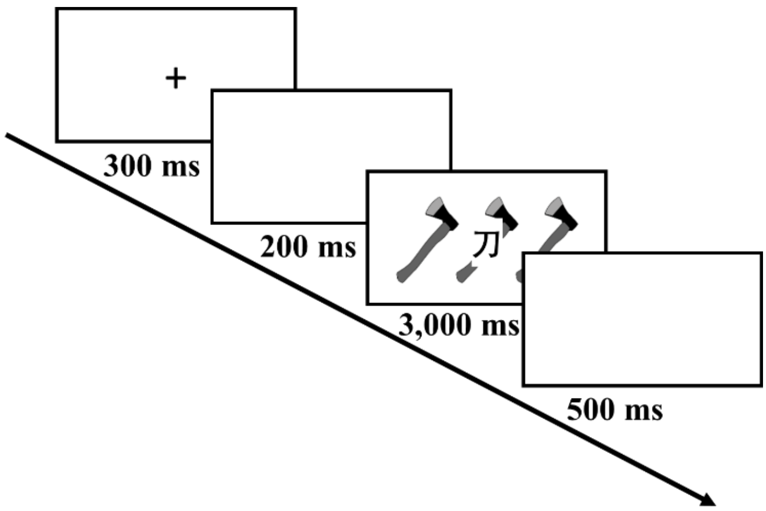


**Figure 2.1**. Sequence of stimulus presentation.

## 2.2.4. EEG recordings and data pre-processing

EEG data were recorded using a mobile Active-Two BioSemi system (BioSemi, Amsterdam) installed and configured in a controlled linguistic laboratory environment. Thirty-two Ag/AgCl active electrodes were positioned on the EEG cap according to the standardised international 10/20 system (see Appendix 2.B). In addition, six external electrodes were used: two were placed at the outer canthi of the eyes to record horizontal electrooculogram (HEOG), two were positioned above and below the left eye to record vertical electrooculogram (VEOG), and two were attached to the left and right mastoids to allow for offline re-referencing. The Common Mode Sense (CMS) and Driven Right Leg (DRL) electrodes served as the online reference and ground, respectively, to reduce noise and enhance signal quality. EEG signals were sampled at 512 Hz.

EEG data pre-processing and ERP extraction were performed offline using BrainVision Analyzer (Version 2.2.2, Brain Products GmbH, Gilching, Germany), following the procedure outlined in Von Grebmer zu Wolfsthurn et al. (2021). Raw EEG signals were re-referenced to the average of the mastoid electrodes and band-pass filtered from 0.1 to 30 Hz. A notch filter at 50 Hz was applied to eliminate powerline interference. Noisy channels, constituting between 3.13% and 12.5% of electrodes per participant (mean = 6.92%), were corrected using spherical spline interpolation. Ocular artefacts were identified through combined HEOG and VEOG channels using linear derivation and corrected via independent component analysis (ICA). Trials with voltage fluctuations exceeding ±100 μV or containing other artefacts were excluded. Epochs were segmented for correctly named trials, from -200 ms to 800 ms relative to picture onset. Baseline correction was applied based on the mean voltage in the 200 ms pre-stimulus interval. Valid epochs were exported for statistical analysis. Five participants were excluded from further analysis due to insufficient valid trials (<60%), resulting in a final dataset of thirty participants.

## 2.2.5. Data Analysis

### 2.2.5.1. Behavioural data analysis

Naming accuracy and latency data were manually checked and extracted using Praat 6.3.08 (Boersma, 2001) and were analysed using a single-trial modelling approach via the R package *lme4* (Bates et al., 2015). Naming accuracy was modelled using generalised linear mixed models (GLMMs) via the *glmer()* function with a binomial distribution. Naming latencies, which showed positive skew, were analysed using *glmer()* with an inverse Gaussian distribution. The fixed-effect predictors in the models included Classifier Congruency and Semantic Relatedness, both sum-coded, with the classifier-incongruent and semantically unrelated conditions serving as reference levels, respectively. Random effects initially included random intercepts for participants and items and random slopes for each fixed effect by participants and by items. A backward elimination strategy was applied to refine the random-effects structure. Simplification was carried out when models failed to converge or additional random effects did not significantly improve model fit (Bates et al., 2015). Model comparison and selection were performed using the *anova()* function, guided by a combination of Akaike's Information Criterion (AIC; Akaike, 1974), Bayesian Information Criterion (BIC; Neath & Cavanaugh, 2012) and log-likelihood ratio tests (Lewis et al., 2011). Model diagnostics included residual plots to assess homoscedasticity and normality.

#### 2.2.5.2. EEG data analysis

We first performed a permutation test on the ERP data before statistical modelling to examine the temporospatial distribution of *classifier congruency* and *semantic interference effects*. Using the *permutes* package (Voeten, 2023b), we computed F-values across all electrodes within the 0 – 700 ms time window relative to stimulus onset. Given that 700 ms post-stimulus onset is approaching the onset of articulation, as evidenced by the behavioural results, the time window for detecting the effects was restricted to before this time point. To assess spatial patterns in the effects, we introduced a factor of Anteriority and grouped electrodes into three regions: anterior (AF3, AF4, F7, F8, F3, F4, Fz), central (FC5, FC6, FC1, FC2, C3, C4, CP5, CP6, CP1, CP2, Cz) and posterior (P7, P8, P3, P4, PO3, PO4, O1, O2, Pz, Oz). Based on the results of the permutation analysis, we identified time windows and regions of interest (ROIs) and then conducted statistical modelling using single-trial linear mixed-effects models (LMMs) using the *lmer()* function (Amsel, 2011; Frömer et al., 2018). Fixed effects included Classifier Congruency, Semantic Relatedness, and Anteriority (all sum-coded). The random-effects structure mirrored the approach used in the behavioural analysis, with backward elimination applied to determine the best-fitting model.

## 2.3. Results

### 2.3.1. Behavioural data exclusion

To maintain consistency with the EEG datasets, five participants were excluded from the behavioural data analysis, whereby a total of thirty datasets were retained. From a total of 6,000 recorded trials collected from the thirty participants, we further excluded 1,355 data points (22.58%) when analysing the naming latencies. The exclusions were implemented in accordance with the following criteria: (1) 394 responses (6.57%) were excluded due to the use of incorrect nouns or classifiers and the absence of responses; (2) 50 trials (0.89%) were excluded for exhibiting naming latencies exceeding 2,000 ms or falling below 200 ms; (3) 79 trials (1.32%) were identified as outliers, given that their naming latencies exceeded three standard deviations from the mean latency for each participant and item; (4) further exclusions were made based on EEG data (as detailed in Section 3.3). As a result, a total of 4,645 trials (77.42%) remained for subsequent analysis.

### 2.3.2. Behavioural data results

#### 2.3.2.1. Naming accuracy

The best-fitting model (see Table 2.2) included the main effects of Classifier Congruency, Semantic Relatedness, and random intercepts for both subjects and items. The analysis revealed (see Figure 2.2) a significant main effect of Classifier Congruency, with naming accuracy significantly lower for classifier-congruent conditions ($M = 0.921$, $SD = 0.269$) compared to incongruent ($M = 0.947$, $SD = 0.223$) conditions ($\beta = -0.240$, $SE = 0.055$, $z = -4.361$, *95% CI* [-0.348, -0.132], $p < 0.001$). A significant effect of Semantic Relatedness was also found, where naming accuracy was lower for semantically related items ($M = 0.925$, $SD = 0.263$) than for unrelated ($M = 0.943$, $SD = 0.23$) items ($\beta = -0.169$, SE = 0.055, $z = -3.068$, *95% CI* [-0.276, -0.061], $p = 0.002$). The interaction between Classifier Congruency and Semantic Relatedness did not reach statistical significance ($\beta = 0.036$, $SE = 0.055$, $z = 0.648$, *95% CI* [-0.072, 0.143], $p = 0.517$).

**Table 2.2**

The best-fitting model for naming accuracy.

**Formula:** naming accuracy ~ 1 + classifier congruency × semantic relatedness + (1 | subject) + (1 | item)

| *Predictors* | *log-odds* | *std. error* | *95%CI* | *z-value* | *Pr(>\|z\|)* |
|---|---|---|---|---|---|
| (Intercept) | 3.198 | 0.234 | 2.739 – 3.657 | 13.653 | **<0.001** |
| Classifier[Congruent] | -0.240 | 0.055 | -0.348 – -0.132 | -4.361 | **<0.001** |
| Semantic[Related] | -0.169 | 0.055 | -0.276 – -0.061 | -3.068 | **0.002** |
| Classifier[Congruent] × Semantic[Related] | 0.036 | 0.055 | -0.072 – 0.143 | 0.648 | 0.517 |
| **Random Effects** | | | | | |
| $\sigma^2$ | 3.29 | | | | |
| $\tau_{00\ Subject}$ | 0.55 | | | | |
| $\tau_{00\ Item}$ | 0.75 | | | | |
| ICC | 0.28 | | | | |
| $N_{Subject}$ | 30 | | | | |
| $N_{Item}$ | 25 | | | | |
| Observations | 6,000 | | | | |
| Marginal $R^2$ / Conditional $R^2$ | 0.019 / 0.298 | | | | |

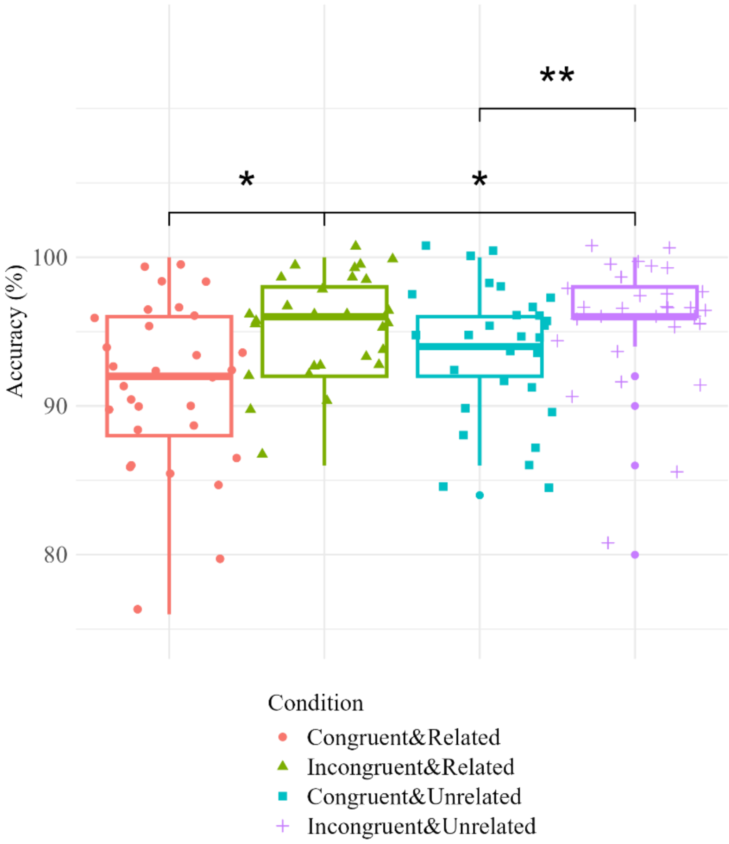



**Figure 2.2.** Naming accuracy (%) for each condition.

#### 2.3.2.2. Naming latencies

The best-fitting model of naming latencies, as shown in Table 2.3 and Figure 2.3, indicated a significant main effect of Semantic Relatedness ($\beta$ = 9.388, *SE* = 4.325, *95% CI* [0.909, 17.867], *p* = 0.03). Specifically, naming latencies were longer in the semantically related condition (*M* = 1,029 ms, *SD* = 248) compared to the semantically unrelated condition (*M* = 1,013 ms, *SD* = 241). No main effect was found for Classifier Congruency — naming latencies did not differ significantly between classifier-congruent (*M* = 1,021 ms, *SD* = 248) and classifier-incongruent (*M* = 1,021 ms, *SD* = 241) conditions ($\beta$ = -0.161, *SE* = 4.153, *95% CI* [-8.303, 7.980], *p* = 0.969). A significant interaction between Classifier Congruency and Semantic Relatedness was observed ($\beta$ = -10.580, *SE* = 5.286, *95% CI* [-20.944, -0.217], *p* = 0.045). Post-hoc analyses were conducted using the *emmeans* package (Lenth, 2024). For semantically related items, naming latencies were significantly shorter for classifier-congruent trials (*M* = 1,020 ms, *SD* = 249) than incongruent (*M* = 1,038 ms, *SD* = 247) trials ($\beta$ = -21.5, *SE* = 10.5, *z* = -2.043, *95% CI* [-42.1, -0.872], *p* = 0.041). For semantically unrelated pairs, however, there was no significant difference in naming latencies between classifier-congruent and incongruent trials ($\beta$ = 20.8, *SE* = 15.8, $z$ = 1.315, *95% CI* [-10.2, 51.887], $p$ = 0.188).

**Table 2.3**

The best-fitting model for naming latencies.

**Formula:** naming latencies ~ 1 + classifier congruency × semantic relatedness + (1 + classifier congruency × semantic relatedness | subject) + (1 | item)

| *Predictors* | *Estimates* | *std. error* | *95%CI* | *Pr(>\|z\|)* |
|---|---|---|---|---|
| (Intercept) | 1054.762 | 21.866 | 1,011.895 – 1,097.630 | **<0.001** |
| Classifier[congruent] | -0.161 | 4.153 | -8.303 – 7.980 | 0.969 |
| Semantically[related] | 9.388 | 4.325 | 0.909 – 17.867 | **0.030** |
| Classifier[congruent] × Semantically[related] | -10.580 | 5.286 | -20.944 – -0.217 | **0.045** |
| **Random Effects** | | | | |
| $\sigma^2$ | 0.01 | | | |
| $\tau_{00\ \text{Subject}}$ | 2,106.02 | | | |
| $\tau_{00\ \text{Item}}$ | 882.14 | | | |
| $\tau_{11\ \text{Subject.ClassifierCongruent}}$ | 101.85 | | | |
| $\tau_{11\ \text{Subject.SemanticallyRelated}}$ | 135.46 | | | |
| $\tau_{11\ \text{Subject.ClassifierCongruent:SemanticallyRelated}}$ | 230.52 | | | |
| $\rho_{01\ \text{Subject.ClassifierCongruent}}$ | -0.06 | | | |
| $\rho_{01\ \text{Subject.SemanticallyRelated}}$ | 0.18 | | | |
| $\rho_{01\ \text{Subject.ClassifierCongruent:SemanticallyRelated}}$ | -0.09 | | | |
| ICC | 1.00 | | | |
| $N_{\text{Subject}}$ | 30 | | | |
| $N_{\text{Item}}$ | 25 | | | |
| Observations | 4,645 | | | |

| | |
|---|---|
| Marginal $R^2$ / Conditional $R^2$ | 0.055 / 1.000 |

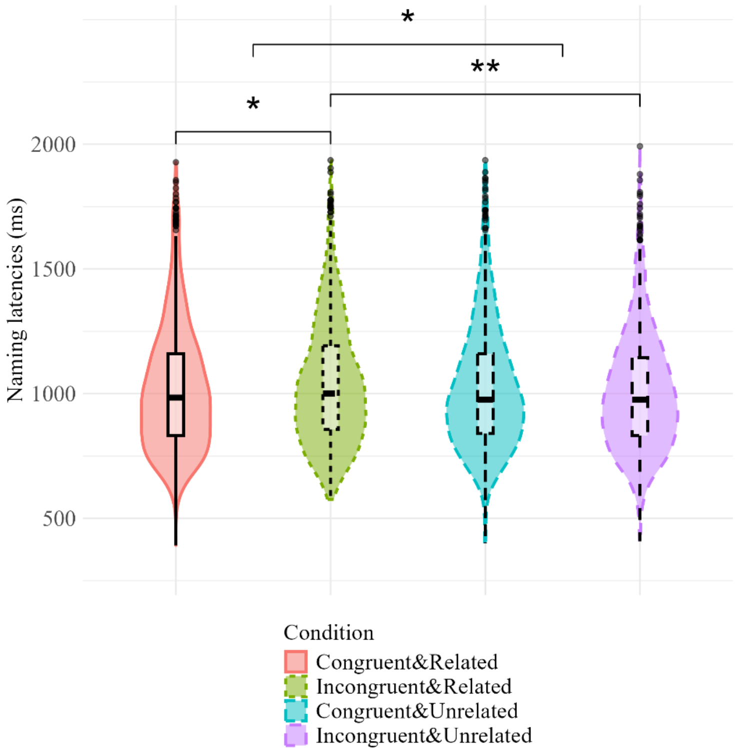



**Figure 2.3.** Naming latencies (in ms) for each condition.

## 2.3.3. EEG data exclusion

The EEG data analysis was conducted following the same exclusion criteria as those applied to the behavioural analysis, including trials with incorrect responses and outliers. 15.02% of the EEG data was contaminated by artefacts, which were removed during data pre-processing. Thirty datasets were analysed with the same fixed effects as in the behavioural analysis.

## 2.3.4. EEG data results

Visual inspection of the permutation test results indicated a potential modulatory effect of Classifier Congruency in the frontal region (Fz) and centro-parietal region (Pz, PO4, P8, P3, Oz, O2, Cz, CP5) between 400 ms and 500 ms post-stimulus onset, as well as an effect of Semantic Relatedness in the fronto-central region (Fz, FC2, FC1, F8, F7, F4, F3, Cz) emerging between 350 ms and 550 ms post-stimulus onset (see Figure 2.4).

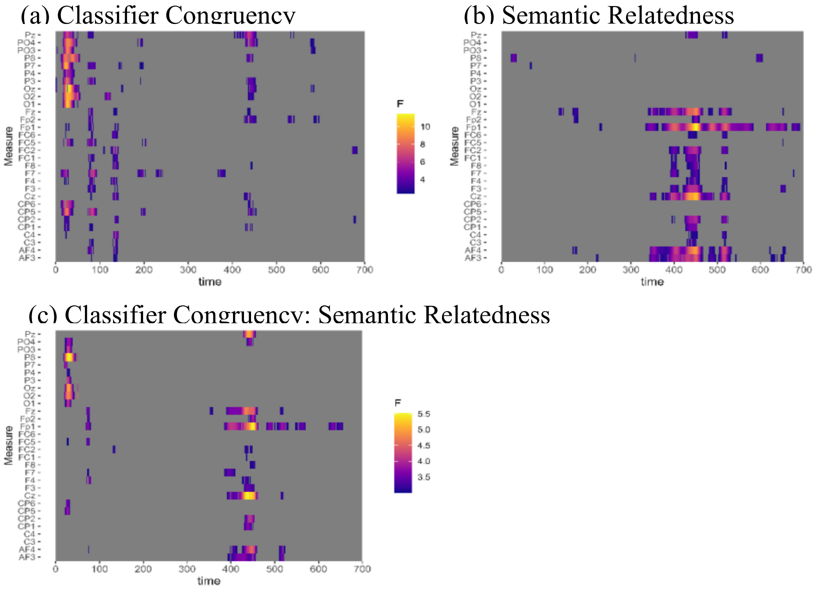



**Figure 2.4.** Outcomes of the permutation test performed on all electrodes for the 0 – 700 ms time window relative to stimulus onset.

We modelled the voltage amplitudes from 400 to 500 ms post-stimulus onset based on the time window identified in the permutation test for the potential *classifier congruency effect.* The best-fitting model (see Table 2.4) showed a significant main effect of Semantic Relatedness ($\beta$ = 0.285, *SE* = 0.139, $t$ = 2.053, *95% CI* [0.013, 0.557], $p$ = 0.040) with less positive voltage amplitudes for semantically unrelated conditions ($M$ = 2.984 µV, *SD* = 12.771) compared to related conditions ($M$ = 3.616 µV, *SD* = 13.015); There was a trend for the *classifier congruency effect*, with less positive voltage amplitudes for classifier-incongruent conditions ($M$ = 3.020 µV, *SD* = 12.836) than classifier-congruent ($M$ = 3.584 µV, *SD* = 12.953) conditions ($\beta$ = 0.248, *SE* = 0.134, $t$ = 1.850, *95% CI* [0.015, 0.511], $p$ = 0.064). Post-hoc analysis showed that the effect of Classifier Congruency was significant in the anterior region ($\beta$ = 0.533, *SE* = 0.268, $z$ = 1.984, *95% CI* [0.007, 1.061], $p$ = 0.047), but not in the others. The interaction between Semantic Relatedness and Anteriority was significant ($F$(2, 2656788) = 175.25, $p$ < 0.001). Post-hoc analysis showed that the effect of Semantic Relatedness was significant in the anterior ($\beta$ = 0.834, *SE* = 0.278, $z$ = 3.000, *95% CI* [0.289, 1.379], $p$ = 0.003) and central regions ($\beta$ = 0.721, *SE* = 0.278, $z$ = 2.592, *95% CI* [0.176, 1.267], $p$ = 0.010). Figure 2.5 presents the grand mean of the ERPs on a selection of electrodes. Figure 2.6 provides a visual presentation of the effect of Classifier Congruency and Semantic Relatedness using scalp topography.

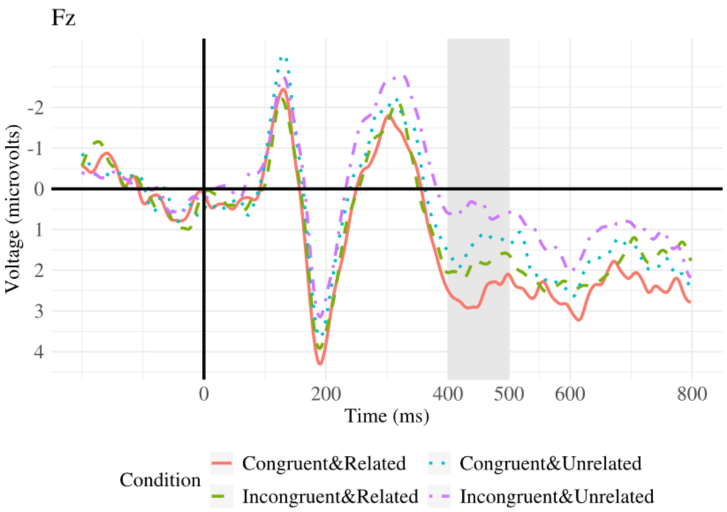
**Table 2.4**

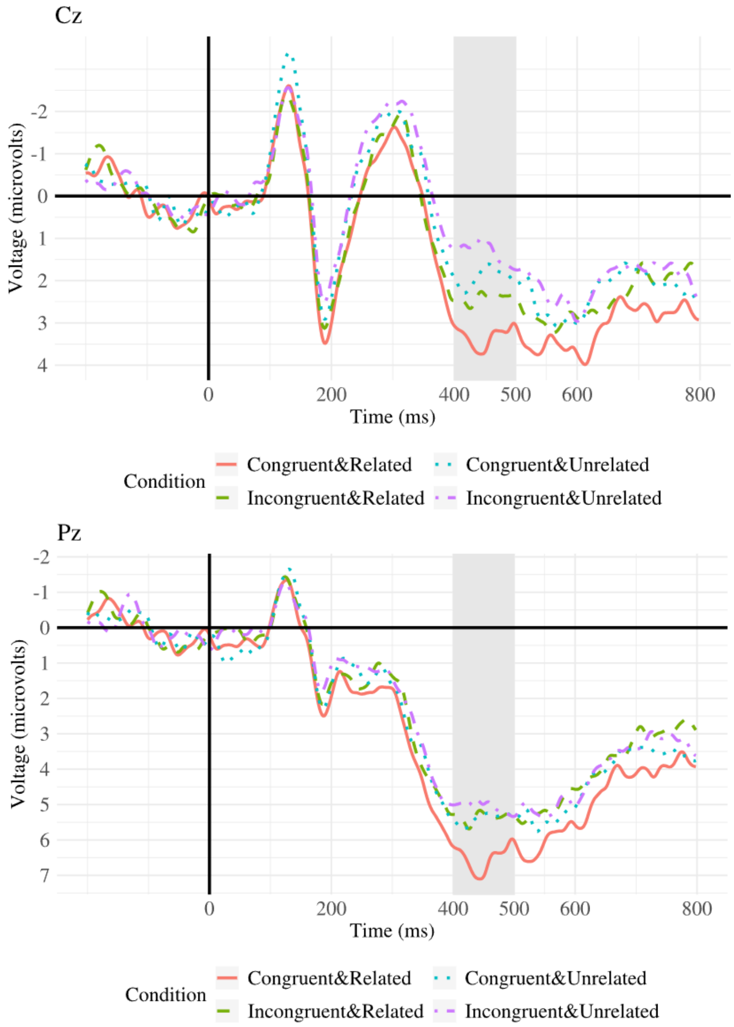
The best-fitting model for voltage amplitudes in the 400 - 500 ms time window post-stimulus onset.

**Formula:** voltage amplitudes ~ 1 + classifier congruency × semantic relatedness × anteriority + (1 + classifier congruency × semantic relatedness | subject) + (1 | item)

| *Predictors* | *Estimates* | *std. error* | *95%CI* | *t-value* | *Pr(>\|t\|)* |
|---|---|---|---|---|---|
| (Intercept) | 3.139 | 0.738 | 1.693 – 4.586 | 4.255 | **<0.001** |
| Classifier[Congruent] | 0.248 | 0.134 | -0.015 – 0.511 | 1.850 | 0.064 |
| Semantic[Related] | 0.285 | 0.139 | 0.013 – 0.557 | 2.053 | **0.040** |
| Anteriority[Posterior] | 1.670 | 0.009 | 1.653 – 1.687 | 192.010 | **<0.001** |
| Anteriority[Central] | -0.400 | 0.010 | -0.419 – -0.381 | -41.560 | **<0.001** |
| Classifier[Congruent] × Semantic[Related] | -0.036 | 0.118 | -0.267 – 0.195 | -0.305 | 0.760 |
| Classifier[Congruent] × Anteriority[Posterior] | -0.023 | 0.009 | -0.040 – -0.006 | -2.677 | **0.007** |
| Classifier[Congruent] × Anteriority[Central] | 0.005 | 0.010 | -0.014 – 0.024 | 0.489 | 0.625 |
| Semantic[Related] × Anteriority[Posterior] | -0.208 | 0.009 | -0.225 – -0.191 | -23.914 | **<0.001** |
| Semantic[Related] × Anteriority[Central] | 0.076 | 0.010 | 0.057 – 0.095 | 7.874 | **<0.001** |
| Classifier[Congruent] × Semantic[Related] × Anteriority[Posterior] | 0.130 | 0.009 | 0.113 – 0.147 | 14.933 | **<0.001** |
| Classifier[Congruent] × Semantic[Related] × Anteriority[Central] | 0.019 | 0.010 | -0.000 – 0.038 | 1.948 | 0.051 |
| **Random Effects** | | | | | |
| $\sigma^2$ | | | 147.14 | | |
| $\tau_{00\ \mathrm{Subject}}$ | | | 15.40 | | |

| | |
|---|---|
| $\tau_{00}$ Item | 0.78 |
| $\tau_{11}$ Subject.ClassifierCongruent | 0.54 |
| $\tau_{11}$ Subject.SemanticRelated | 0.58 |
| $\tau_{11}$ Subject.ClassifierCongruent:SemanticRelated | 0.42 |
| $\rho_{01}$ Subject.ClassifierCongruent | 0.24 |
| $\rho_{01}$ Subject.SemanticRelated | 0.05 |
| $\rho_{01}$ Subject.ClassifierCongruent:SemanticRelated | 0.55 |
| ICC | 0.11 |
| N Subject | 30 |
| N Item | 25 |
| Observations | 3,623,100 |
| Marginal $R^2$ / Conditional $R^2$ | 0.011 / 0.117 |





Cz
Voltage (microvolts)
-2
-1
0
1
2
3
4
0
200
400
500
600
800
Time (ms)
Condition
Congruent&Related
Congruent&Unrelated
Incongruent&Related
Incongruent&Unrelated
Pz
Voltage (microvolts)
-2
-1
0
1
2
3
4
5
6
7
0
200
400
500
600
800
Time (ms)
Condition
Congruent&Related
Congruent&Unrelated
Incongruent&Related
Incongruent&Unrelated

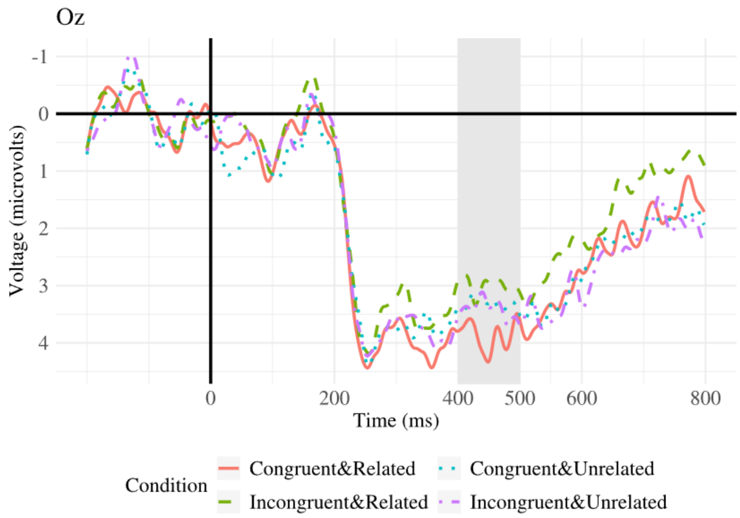



**Figure 2.5.** Grand averages of ERPs from representative electrodes (Fz, Cz, Pz, Oz) for all conditions.

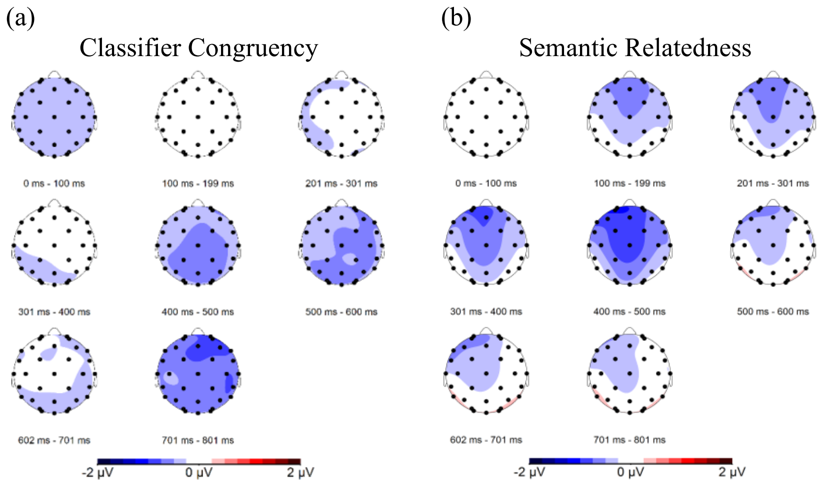



**Figure 2.6.** Scalp topographies every 100 ms after stimulus onset. (a) The difference in voltage amplitudes between the classifier-incongruent condition and the classifier-congruent condition. (b) The difference in voltage amplitudes between the semantically unrelated condition and the semantically related condition.

## 2.4. Discussion

The present study aimed to investigate the processing of classifier information during noun phrase production in Mandarin Chinese. It specifically examined the effects of classifier congruency and semantic relatedness utilizing a picture-word interference (PWI) paradigm. We introduced several methodological refinements based on previous research (Huang & Schiller, 2021; Li et al., 2006; Wang et al., 2019; Zhang & Liu, 2009). These included the exclusion of highly grammaticalised general classifiers (e.g., *gè*), applying single-trial linear mixed-effects modelling and adopting a permutation-based approach for defining EEG time windows in a data-driven manner. By implementing these improvements, we reassess the robustness of the *classifier congruency effect* and gain further insights into its relation to semantic processing.

Consistent with previous findings (e.g., Dell'Acqua et al., 2010; Huang & Schiller, 2021; Krott et al., 2019; Rose et al., 2019; Wang et al., 2019; Zhu et al., 2015), the current study replicated a reliable *semantic interference effect*: naming latencies were significantly longer when the target and distractor words belonged to the same semantic category compared to when they were unrelated. In the electrophysiological data, the semantically unrelated condition elicited more negative voltage amplitudes than the semantically related condition within the N400 time window, a component typically associated with semantic processing difficulty (Kutas & Federmeier, 2011). Regarding the *classifier congruency effect*, although no significant main effect was found on naming latencies across all conditions, a significant interaction between classifier congruency and semantic relatedness emerged. Specifically, classifier incongruency delayed naming significantly when the distractors were semantically related to the target nouns but not when the distractors were semantically unrelated. In the ERP data, although the main effect of classifier congruency only approached statistical significance across all regions within the 400-500 ms time window, further regional analyses revealed a significant *classifier congruency effect* in the anterior scalp region.

The *semantic interference effect* observed in behavioural and ERP data aligns with a large body of literature demonstrating semantic processing during lexical retrieval (Bürki et al., 2020). According to the prominent model of lexical access (Levelt et al., 1999a; Roelofs, 1992), when participants attempt to name a target picture, activation initially spreads from the conceptual representation of the target to semantically related concepts within the network (see also Bloem & La Heij, 2003; Lupker, 1979; Roelofs, 1992; Schnur et al., 2006). This activation then spreads to the corresponding lemma nodes. Consequently, when distractors are semantically related to the target, their lexical nodes are activated to a higher level compared to unrelated distractors. During lemma selection, these co-activated lexical candidates compete with the target lemma, leading to increased selection difficulty and extended naming latencies.

The present study also observed a *classifier congruency effect* in the naming latencies under the semantically related condition. Wang et al. (2019) propose that the *classifier congruency effect* is similar to the *gender congruency effect* observed in some Indo-European languages. According to their account, the *classifier congruency effect* reflects the activation of classifiers as lexico-syntactic features during lemma access, thereby supporting speech production models such as proposed by Levelt et al.'s (1999a). In this framework, the associated classifier nodes are automatically activated when the target and the distractor are processed. When these classifiers are incongruent, this activation leads to competition for selection, which is behaviourally observed as prolonged naming latencies.

Notably, the *classifier congruency effect* observed in this study was modulated by semantic relatedness. Under semantically related conditions, classifier-incongruent stimuli were named significantly slower than classifier-congruent stimuli. However, this trend did not reach statistical significance under semantically unrelated conditions. This interaction pattern suggests that the competition among incongruent classifier nodes may be stronger in the semantically related condition than the unrelated condition, likely due to increased co-activation of semantically related content nodes and their associated classifier nodes. Compared to the materials in previous studies (Huang & Schiller, 2021; Wang et al., 2019), we excluded the highly grammaticalized general classifier "*gè*", which has largely lost its semantic content. In addition, noun-classifier pairs were carefully selected based on a corpus, ensuring the highest collocation frequencies. These adjustments ensured that the classifiers used in the experiment preserved semantic content and that the semantic associations between nouns and classifiers were relatively strong.

Zhang and Liu (2009) pointed out that, unlike grammatical gender systems, which often exhibit one-to-one mappings between nouns and gender markers, the relationship between nouns and classifiers in Mandarin is many-to-many. A single classifier can be associated with numerous nouns, and a noun may take different classifiers to highlight varying semantic nuances (e.g., "*yí shù huā*, a bouquet of flowers" vs. "*yì duǒ huā*, a single flower"). The classifier-noun pairs selected for the current experiment exhibited high collocation frequency, which typically indicates a substantial overlap in their semantic features. Furthermore, compared to morphologically rich languages, Mandarin Chinese syntax is more heavily constrained by semantic relations. Consequently, it is plausible that the activation and selection of classifier nodes in Mandarin are also influenced by semantic processing. A common interpretation of the *semantic interference effect* (Bürki et al., 2020) is that activation spreads from the target noun's concept node (e.g., *hóuzi*, "monkey") to semantically related concepts (e.g., *mǎ*, "horse"; *xióngmāo*, "panda") and their corresponding lexical entries. This process may subsequently enhance the activation of classifier nodes closely associated with the co-activated lexical candidates (e.g., classifier *pǐ* for *mǎ*; classifier *zhī* for *xióngmāo*), thereby increasing competition for lexical selection between the incongruent classifiers of the distractor (e.g., classifier *pǐ* for *mǎ*) and the target word (e.g., classifier *zhī* for *hóuzi*).

Although the classifier processing appears to be influenced by semantic processing, the timing of the *semantic interference effect* and the *classifier congruency effect* may differ slightly. Both effects are generally reported to occur within the N400 time window (Huang & Schiller, 2021; Wang et al., 2019). The ERP data from the present study generally supports this view. Nonetheless, based on the permutation test results and the scalp topographies, although both effects peaked within the N400 time window, the *semantic interference effect* emerged slightly earlier than the *classifier congruency effect*. This temporal difference further validates the aforementioned findings in previous studies and supports the interpretations offered in the current study. Specifically, the *semantic interference effect* appears to arise during concept-lexical activation stages (Abdel Rahman & Melinger, 2009; Bloem & La Heij, 2003; Zhang et al., 2016). In contrast, the *classifier congruency effect* emerges slightly later, during lemma access and the retrieval of lexico-syntactic features. Together, these findings contribute to a finer-grained understanding of the temporal dynamics underlying classifier and semantic processing during Mandarin Chinese noun phrase production.

## 2.5. Conclusions

This study investigated whether the *classifier congruency effect* could be reliably elicited during noun phrase production in Mandarin Chinese and how this effect relates to semantic processing. By employing refined experimental materials and advanced analytical approaches, the present study provides further evidence for the automatic activation of classifiers during lemma access. Furthermore, the results indicate that classifier processing emerges slightly later than the *semantic interference effect* and that semantic processing may modulate classifier activation. Future research could build on these findings by exploring how different classifiers (e.g., specific classifiers versus general classifiers) differentially engage semantic and syntactic processing streams.

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## Declaration of interest statement

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

## Author contributions

**Jin Wang**: conceptualisation, methodology, programming, data acquisition, formal analysis, data curation, writing-original draft, writing-review and editing, funding acquisition. **Jurriaan Witteman**: formal analysis, writing-review and editing, supervision. **Niels O. Schiller**: conceptualisation, methodology, writing-review and editing, supervision, funding acquisition.

# Appendix

## 2.A Model parameters: Semantic relatedness rating scores

**Table 2.A.1** Model of best fit for rating scores, including log-odds ratios, standard errors, confidence intervals, z-values and p-values (n = 15).

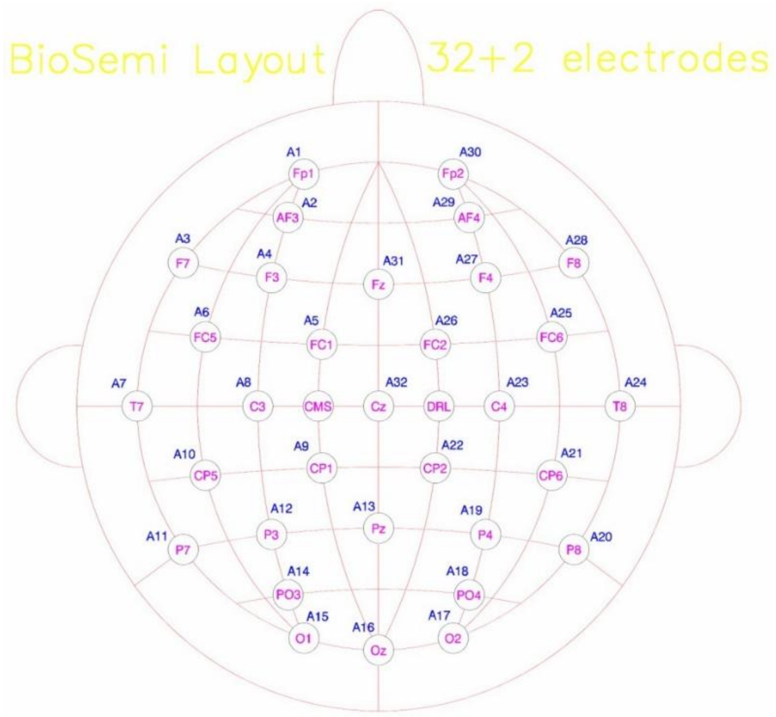
**Formula:** rating score ~ semantic relatedness + classifier congruency + (1 + semantic relatedness | subject) + (1 | item)

| *Predictors* | *log-odds* | *std. error* | *95% CI* | *z-value* | *Pr(>\|z\|)* |
|---|---|---|---|---|---|
| 1\|2 | -2.677 | 0.263 | -3.192 – -2.162 | -10.191 | **<0.001** |
| 2\|3 | -1.158 | 0.259 | -1.666 – -0.649 | -4.463 | **<0.001** |
| 3\|4 | -0.185 | 0.258 | -0.692 – 0.321 | -0.718 | 0.473 |
| 4\|5 | 0.049 | 0.258 | -0.457 – 0.556 | 0.192 | 0.848 |
| 5\|6 | 1.495 | 0.260 | 0.985 – 2.004 | 5.750 | **<0.001** |
| 6\|7 | 3.218 | 0.264 | 2.700 – 3.736 | 12.180 | **<0.001** |
| Semantic relatedness [related] | 3.831 | 0.359 | 3.127 – 4.535 | 10.666 | **<0.001** |
| Classifier congruency [congruent] | 0.070 | 0.059 | -0.046 – 0.185 | 1.180 | 0.238 |
| **Random Effects** | | | | | |
| $\sigma^2$ | 3.29 | | | | |
| $\tau_{00\ \mathrm{Item}}$ | 0.33 | | | | |
| $\tau_{00\ \mathrm{Subject}}$ | 1.58 | | | | |
| $\tau_{11\ \mathrm{Subject.Semantic\ relatednessUnrelated}}$ | 6.57 | | | | |
| $\rho_{01\ \mathrm{Subject}}$ | -0.84 | | | | |
| ICC | 0.37 | | | | |
| $N_{\mathrm{Subject}}$ | 15 | | | | |
| $N_{\mathrm{Item}}$ | 25 | | | | |
| Observations | 1,453 | | | | |

| | |
|---|---|
| Marginal $R^2$ / Conditional $R^2$ | 0.835 |

## 2.B EEG montage

**Figure 2.B.1:** 32-channels with 10/20 system layout including CMS and DRL (www.biosemi.com/headcap.htm).



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