Title
Neural decoding of words and morphosyntactic features within and across languages

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 46(0)

Authors
Cho, Jeonghwa
Brennan, Jonathan R.

Publication Date
2024

Peer reviewed

Neural decoding of words and morphosyntactic features within and across languages

Jeonghwa Cho (jeonghwa@umich.edu)
Department of Linguistics, University of Michigan

Jonathan R. Brennan (jobrenn@umich.edu)
Department of Linguistics, University of Michigan

Abstract

This paper tests the similarity in neural responses across repeated words and morphosyntactic features both within and between two languages. Prior work using priming has revealed robust cross-linguistic lexical effects and effects for shared grammatical form, such as argument structure; these methods have been less successful when applied to morphosyntactic features. Combining machine-learning based neural decoding with EEG data collected from Korean-English bilinguals we, first, replicate prior work showing successful classification of lexical items from EEG signals. We then extend this to demonstrate successful classification of morphosyntactic features of number and tense. Finally, we find that EEG decoding in one language does not successfully generalize to another, even when temporal differences are considered. Taken together, these results point to stable EEG representations for lexical items and morphosyntactic features, but suggest that these representations are different between the two languages investigated here.

Keywords: MVPA, number, tense, lexical concepts, EEG

Introduction

Often the same concept is expressed as different forms in different languages. For example, the concept of a furry, four-legged animal that has a flexible body and retractable claws is referred to by different words in different languages: *cat*, *고양이*, *chat*, and *gato* to name a few. In a similar vein, the grammatical affixes *-ed*, *-ó*, and *-았* all look and sound different but denote the same idea of an action that happened in the past. How do these language-specific variations affect processing of concepts and grammatical forms? Are there commonalities among languages despite such surface differences? The current study aims to examine cross-linguistic neural representations of words and morphosyntactic features by conducting a multi-voxel pattern analysis (MVPA) on EEG data collected from Korean-English bilinguals.

Whether bilinguals have language-independent shared representations of lexical concepts has been a core research area in bilingualism. Cross-linguistic lexical priming paradigm has been a popular method used to address this question. In this paradigm, a target word is presented after another word, called a prime word. It is known that the relation between the prime and the target word affects the reaction times to decide whether the target word is a real word. A significant number of studies have shown cross-linguistic facilitatory effects for translation equivalents between various languages, including Hebrew and English (Gollan et al., 1997), Chinese and English (Jiang, 1999), Japanese and English (Hoshino et al., 2010), and Korean and English (Cho and Brennan, 2022; Kim and Davis, 2003), supporting the view that between-language words are connected via non-linguistic, language-independent concepts. Studies using neuroimaging methods such as functional magnetic resonance imaging (fMRI) and event-related potentials (ERPs) complement these results, providing neural evidence for the integrated nature of bilingual lexicon. For example, Chee et al. (2000) and Xue et al. (2004) show overlapping brain areas in processing English and Chinese words.

Similarly, a widely accepted view on bilingual representation of morphosyntactic features is that they are also shared between languages. For instance, the *shared syntax account* (Hartsuiker et al., 2004; Hartsuiker and Bernolet, 2017) posits that words in two different languages not only share the same conceptual representation but also their grammatical characteristics. To be more specific, in this model, translation-equivalent words in different languages are connected to the same *conceptual* node (e.g., HIT (X, Y)), *combinatorial* node (e.g., active, passive), and *category* node (e.g., verb). Each individual word is further linked to a *language* node (e.g., English, Spanish…). This model has been successful in accounting for cross-linguistic syntactic priming effects (e.g., Hartsuiker et al., 2016; Kantola and van Gompel, 2011; Shin and Christianson, 2009), where presenting a syntactic structure in one language (e.g., passive) increases the probability of producing the same syntactic structure in another language.

There has been relatively less work on other types of morphosyntactic features, however, such as whether a noun is singular or plural, or a verb is in present or past tense. Employing the priming paradigm for these morphosyntactic features faces challenges as they are often realized as suffixes, which yield little priming effects even within the same language (c.f., [Anonymized] under review for a meta-analysis). As such, the present study uses a different approach to probe bilingual representations for both morphosyntactic features lexical concepts, namely neural decoding, also called MVPA.

With the development of machine learning techniques, MVPA has been actively applied to find multivariate associations between brain activity and a given stimuli (see Haxby et al., 2014 for a review). Unlike traditional univariate analysis methods, multivariate analysis makes use of

In L. K. Samuelson, S. L. Frank, M. Toneva, A. Mackey, & E. Hazeltine (Eds.), *Proceedings of the 46th Annual Conference of the Cognitive Science Society*.

information about the spatial, or spatio-temporal, patterns of the neural signals. In this analysis, a classifier is trained with neural data to discriminate between two or more stimulus features; it is tested with unseen data from which it predicts the stimulus feature based on patterns of neural data. Starting from the success in identifying categories of pictured objects from neural recordings in earlier studies (Carlson et al., 2003; Cox and Savoy, 2003), the method has been extended to identifying word meanings (Chan et al., 2011; Huth et al., 2016; Mitchell et al., 2008; Shinkareva et al., 2011; Simanova et al., 2010) as well as grammatical categories (Boylan et a., 2014; Datta and Boulgouris, 2021) and argument structures (Allen et al., 2012).

MVPA can also be applied to cross-linguistic research to determine whether language processing in different languages involves common neural patterns. For instance, several studies report successful neural decoding of lexical concepts across languages, indicating language-independent neural representations (Buchweitz et al., 2012; Correia et al., 2014, 2015; Zinszer et al., 2015, 2016). In particular, Correia et al. (2015) presented Dutch-English bilinguals with four animal words (bull/stier, duck/eend, horse/paard, and shark/haai) using EEG. In contrast to a univariate analysis that did not reveal any difference in the evoked EEG response between individual animal words, above-chance accuracies were obtained with MVPA spanning 50-620 ms (peak accuracy = 0.537 at 225 ms; chance accuracy = 0.5) after word onset for within-language classification. Across-language classification was successful in short (550-600 and 850-900 ms, accuracy = 0.51). They also report that low frequency bands (< 12 Hz, alpha, theta, and delta) were particularly crucial to obtain high decoding accuracy, as filtering them out significantly decreased classification performance. These results are in line with previous studies (e.g., Bastiaansen et al., 2005; Lam et al., 2016; Momsen and Abel, 2022) that suggest that these frequency bands are associated with lexical and semantic retrieval of words.

While neural decoding of morphosyntactic features across languages has not been yet conducted, this technique can be especially useful to probe the matter of bilingual representation of morphosyntactic features, given the challenges associated with traditional behavioral measures as mentioned above.

Building upon this background, the current study has two primary goals. The first goal is to specify the temporal and frequency profile for neural decoding of lexical items in English and Korean and examine whether there is overlap. This includes cross-languages neural decoding to see whether the results in Correia et al. (2015) are replicated with Korean-English bilinguals. The second goal is to extend this method to morphosyntactic features, i.e., number and tense, in English and Korean. Applying MVPA to EEG data in this sense will enable us to determine i) whether there is any language-independent neural representation of these morphosyntactic features and if so, ii) at which time point and frequency band the information is processed during language comprehension. To this end, Korean-English bilinguals are presented with English and Korean nouns (for lexical decoding and the grammatical feature of number) and verbs (for lexical decoding and the grammatical feature of tense) while their EEG data are recorded. The methodology involves training a classifier on one language to distinguish between different lexical items and morphosyntactic features, such as singular versus plural nouns and present versus past tense verbs. Subsequently, this classifier is tested on the other language to examine the cross-linguistic generalizability of neural representations of these features.

Method

Participants

Fifteen Korean-English bilinguals (7 males, 8 females, 0 others; mean age = 21.57 (SD = 3.50)) were recruited in Ann Arbor, Michigan. They were "early bilinguals" who were born in a Korean-speaking family and moved to the US before puberty (mean age = 5.60, SD = 3.94). They reported that they learned Korean from birth and English at the age of 4.53 (SD = 2.67) on average. Their language background is summarized in Table 1. English proficiency was measured with the Lexical Test for Advanced Learners of English (LexTALE; Lemhöfer & Broersma, 2012) and Korean proficiency was measured using the Korean C-Test (Lee-Ellis, 2009). Finally, language dominancy was determined based on the Bilingual Language Profile (BLP; Birdsong, Gertken, & Amengual, 2012).

Table 1. Language background of participants

AoA	LOR*	English LexTALE (100)	Korean C-Test (100)	BLP
4.53 (2.67)	15.5 (4.67)	85.45 (13.97)	80.67 (16.40)	32.01 (37.55)

* Length of residence (yrs) in the US
Note. SD in parentheses

Stimuli

Four nouns and four verbs were used as stimuli (Table 2). Following Correia et al (2015), noun stimuli consisted of four animal names: "duck", "goat", "swan", and "lion". These nouns were presented in both singular and plural forms. All nouns in the singular form have four letters in English and two syllables in Korean. When in the plural form, they have five letters in English and three syllables in Korean (the plural form is realized by adding a letter -s in English and a syllable *-deul* in Korean. Verb stimuli consisted of four action verbs that are monosyllabic in English and trisyllabic in Korean: "leans/leaned", "cools/cooled", "helps/helped", and "fills/filled".

Table 2. Stimuli used in the experiment.

Nouns			
Singular		Plural	
English	Korean	English	Korean
duck	오리 ori	ducks	오리들 ori-deul
goat	염소 yeomso	goats	염소들 yeomso-deul
swan	백조 baekjo	swans	백조들 baekjo-deul
lion	사자 saza	lions	사자들 saza-deul
Verbs			
Present		Past	
English	Korean	English	Korean
Leans	기댄다 gidaenda	leaned	기댔다 gidaessda
cools	식힌다 sikhinda	cooled	식혔다 sikhyessda
helps	돕는다 dopneunda	helped	도왔다 dowassda
fills	채운다 chaeunda	filled	채웠다 chaewossda

Procedure

Participants completed English and Korean proficiency tests, a handedness survey, and BLP before the experiment. The LexTALE was used to measure English proficiency; this test consists of 40 words and 20 nonwords, and participants are asked to decide whether each string of words is a word or not. For Korean proficiency, the Korean C-test was used, which has four passages with blanks for participants to fill in.

Then participants were seated in front of a monitor screen in a sound-attenuated room. Experiment stimuli were visually presented using Psychopy (Peirce et al. 2019). The experiment had a practice session of 16 English trials and 16 Korean trials followed by the main experiment session. The main session had nine runs, with an English block a Korean block in alternating order per run.

In each block, 32 animal nouns (4 words × 2 forms (singular or plural) × 4 repetitions) and 32 action verbs (4 words × 2 forms (present or past) × 4 repetitions) were presented. In each trial, a cross appeared on the center of the screen for 1.8 – 2.2 seconds followed by a word presented for 500 ms. Also, ten percent of trials were followed by a question mark which prompted participants to judge whether the word is a noun or a verb. The experiment took approximately 60 minutes to complete.

Data acquisition and preprocessing

EEG data were recorded with a sampling rate of 500 Hz from 31 active electrodes (actiCHamp, BrainProducts GMBH) relative to a right mastoid reference electrode. Impedance levels were kept below 15 kΩ. Eye movements and heart beats were monitored with additional electrodes attached to above and below the left eye and on the right wrist.

Data preprocessing was conducted using the MNE-Python package (Gramfort et al., 2013). Data were filtered by a range of 1-30 Hz and separated into epochs time-locked to word onset (-300 to 1000 ms), corrected to baseline (-300 to 0 ms). Artifacts due to eye blinks or movements were removed by Independent Component Analysis and remaining artifacts were removed manually by visual inspection.

Temporal windows analysis

EEG data from one participant was excluded due to low signal-to-noise ratio. For the remaining fourteen participants, data analysis was conducted on trials that did not require participants to respond to a question (90% of all trials). Multivariate analysis was performed using MNE-Python scikit-learn (Pedregosa et al., 2011). An LDA (linear discriminant analysis) classifier was employed for both within-language classification and across-language classification. EEG data were resampled at 100 Hz, filtered using the Xdawn algorithm (Rivet et al., 2009) with default parameters, and then standardized. For each epoch, data were decoded in a moving time-window with a width of 200 ms in 100 ms intervals from -300 to 1000 ms after onset. For within-language classification, accuracy scores were computed by averaging accuracies in a five-fold cross-validation. For across-languages classification, the classifier was trained on data from one language and tested on data from the other language, for each participant.

Classifiers for decoding nouns and verbs had four classes to identify (chance accuracy = 0.25) and classifiers for number (singular vs plural) and tense (present vs past) were binary (chance accuracy = 0.5). For all analyses, statistical significance was tested by cluster-based permutation tests with 10,000 permutations using the *permutation_cluster_1samp_test* function in MNE-Python.

Time frequency analysis

To determine the effect of each frequency band on decoding performance, we removed band-limited frequency information prior to the temporal windows analysis (Correia et al., 2015). In this method, the original epochs were filtered using an FIR (finite impulse response) band stop filter in MNE-Python and the result was used as training and testing dataset. The filtered-out frequency band ranged from 2 Hz to 30 Hz with a 4 Hz width, resulting in 13 filtered signals. The significance of each frequency band was examined by statistically comparing the decoding accuracy from the filtered epochs with the decoding accuracy from the original unfiltered epochs with a cluster-based permutation test.

RESULTS

Temporal windows analysis

Within-languages decoding

Figures 1 shows lexical decoding accuracy over time for nouns and verbs. Cluster-based permutation tests show that decoding for nouns was significantly above chance (0.25) from -100 to 500 ms (p = 0.002; peak accuracy = 0.309 at 200-400 ms) for English and from 0 to 400 ms (p = 0.039;

peak accuracy = 0.282 at 200-400ms) for Korean. For verbs, the accuracy was above chance (0.25) between 0 and 400 ms ($p = 0.004$; peak accuracy = 0.307 at 100-300 ms) for English and between 200 and 500 ms ($p = 0.006$; peak accuracy = 0.278 at 300-500 ms) for Korean.

Decoding results for grammatical number (singular versus plural) and tense (present versus past) are presented in Figure 2. Decoding of grammatical number yielded above-chance accuracy (chance = 0.5) for Korean between 0 and 300 ms ($p = 0.035$; peak accuracy = 0.553 at 100-300 ms) and between 500 and 900 ms ($p = 0.008$; peak accuracy = 0.535 at 600-800 ms), but not in English ($p > 0.107$, peak accuracy = 0.540 at -100-100 ms). For grammatical tense, decoding accuracy was above chance (0.5) for both languages: between 600 and 900 ms in English ($p = 0.022$; peak accuracy = 0.532 at 600-800ms) and between 100 and 300 ms in Korean ($p = 0.034$; peak accuracy = 0.535 at 100-300 ms).

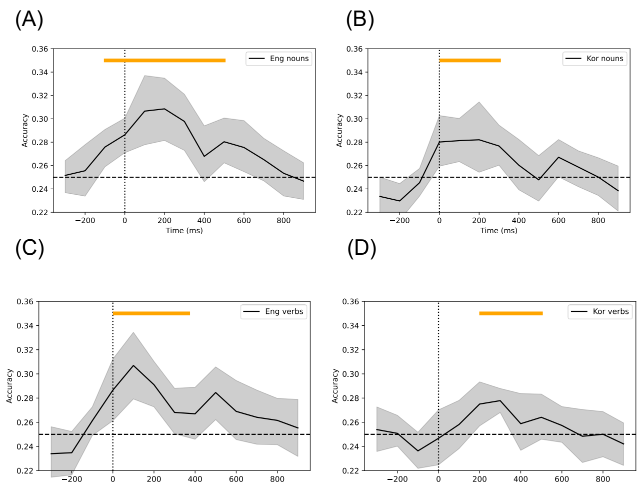

Figure 1. Within-language temporal decoding results for nouns (A and B) and verbs (C and D) (orange bar = $p < 0.05$ in a cluster-based permutation)

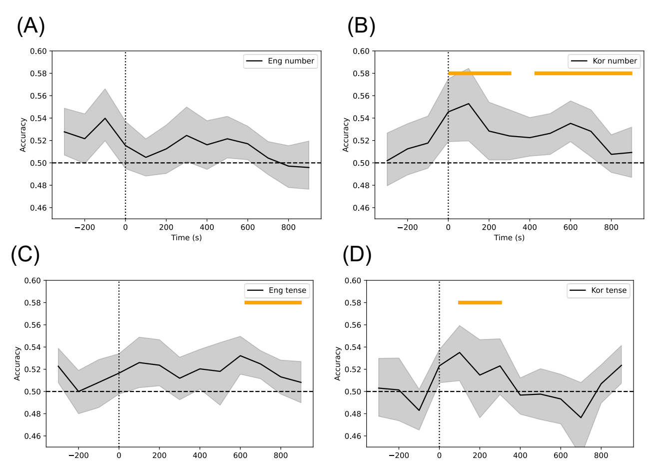

Figure 2. Within-language temporal decoding results of number (A and B) and tense (C and D) (orange bar = $p < 0.05$ in a cluster-based permutation test)

Cross-languages decoding

Cross-languages decoding, on the other hand, did not yield above-chance accuracies for both nouns and verbs, and number and tense in all tested time windows ($ps > 0.216$).

Temporal generalization

Temporal generalization (King and Dehaene, 2014) was conducted for cross-languages decoding to check whether above-chance accuracies may be obtained at different times from each of the two languages. This would indicate that the lexical items and/or morphosyntactic features have overlapping neural representations but are processed at different times in each language. As already noted, decoding of the tense feature yielded above-chance accuracies in each language but at different times (i.e., 600 – 900 ms for English, 100 – 300 ms for Korean). It could thus be the case that cross-languages decoding accuracies were at chance because the training and testing times were confined to the same time window. Temporal generalization was conducted by training a classifier with epochs at each 200 ms-long time window in one language and testing it with epochs in another language across all 200ms-long time windows spanning from -300 ms to 800 ms. See Figure 6 for plotted results for noun and verb decoding and Figure 7 for number and tense decoding.

Statistical significance was tested with cluster-based permutation tests. None of the decoding results were significantly above-chance (English to Korean nouns: $ps > 0.522$, Korean to English nouns: $ps > 0.278$, English to Korean verbs: $ps > 0.307$, Korean to English verbs: $ps > 0.094$). The same null pattern was found for number (English to Korean: $ps > 0.990$, Korean to English: $ps > 0.995$) and tense (English to Korean: $ps > 0.715$, Korean to English: $ps > 0.887$).

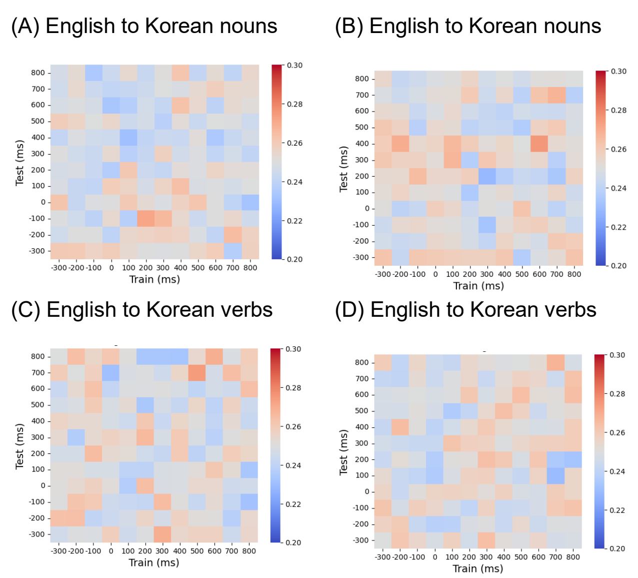

Figure 3. Temporal generalization results from cross-languages decoding of noun (A, B) and verb (C, D) (x axis = training time, y axis = testing time)

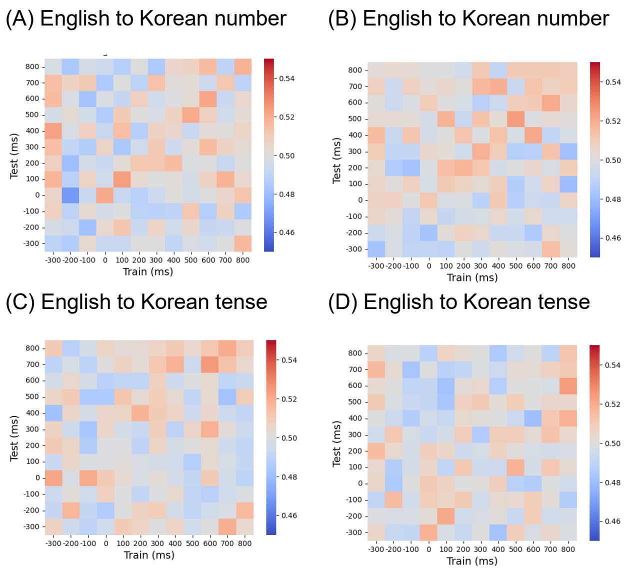

Figure 4. Temporal generalization results from cross-languages decoding of number (A, B) and tense (C, D) (*x*-axis = training time, *y*-axis = testing time)

Time frequency analysis

For time-frequency analysis, the classifier was trained using epochs after filtering out specific frequency bands, allowing us to assess their significance on neural decoding of words and morphosyntactic features. Notably, filtering out the 2-6 Hz frequency band led to a significant decrease in classification performance for English nouns between 100 and 400 ms ($p = 0.001$). Conversely, filtering out the 8-12 Hz band negatively impacted the performance for Korean nouns between 200 and 500 ms ($p = 0.021$). Filtering did not affect decoding accuracies for verbs in either language.

For morphosyntactic features, a frequency band of 8-12 Hz was revealed to be relevant for decoding Korean number between 700-900 ms ($p = 0.043$), and 4-8 Hz for Korean tense between 0-200 ms ($p = 0.046$). Decoding performance for English number and tense was not affected by filtering. Also, filtering out frequency bands did not have a discernible impact on the performance for cross-languages decoding.

Discussion

The current study tests whether lexical concepts and morphosyntactic features can be decoded within language ands well as cross-linguistically. EEG data were collected from Korean-English bilinguals while they silently read English and Korean nouns and verbs. Within-language neural decoding was successful for nouns, verbs, and tense for both languages and for number for Korean.

The time window where above-chance accuracy is obtained for lexical items generally overlaps for nouns and verbs across the two languages, roughly from visual onset until 400 ms or 500 ms. This time window is also similar to the one reported in Correia et al. (2015) for decoding English and Dutch nouns that were presented auditorily, which spanned from the onset to approximately 620 ms. This time period includes processing of low-level visual properties (~100 ms; Hauk et al., 2006), lexicality (150-200 ms; Pulvermüller et al., 1995), and semantic properties (300-600 ms; Kutas and Hillyard, 1980).

Decoding of morphosyntactic features was possible during shorter time windows. For grammatical number, the accuracy was above chance only for Korean, during early (0-300 ms) and late (500-900 ms) time windows. While the early time window may reflect visual and lexical processing, the late time window corresponds to where grammatical processing has been observed. For instance, agreement violations of number and gender yield more positive amplitudes at around 500 ms from onset (the "P600" ERP component; e.g., Barber and Carreiras, 2005; Chen et al., 2007). The current results align with these findings that this time window is involved with grammatical number encoding. English number, on the other hand, did not yield above-chance accuracies. One possible reason for the discrepancy between English and Korean number decoding is a difference in the saliency of the plural marker in the two languages; it is realized as one syllable -*duel* (corresponding to one character -들 in writing) in Korean whereas it is just one letter -*s* in English. It may be the case that the current decoding method is not sensitive enough to capture processing differences deriving from such a minimal visual feature.

Decoding grammatical tense yielded above-chance accuracies for both languages, but at different time windows: between 600-900 ms in English and 100-300 ms in Korean. The time window for decoding English overlaps with that for Korean number, suggesting that processing of English tense also has grammatical nature. The time window for Korean tense, however, is much earlier. In fact, this time period corresponds to where word category has been shown to be processed (Yudes et al., 2016), which the authors interpret to be a marker of morphological processing. Hence, decoding grammatical tense in both languages reflects morphological/grammatical processing, while the distinct time windows may be due to morphosyntactic differences between the languages (tense is realized as a suffix in English versus root conjugation in Korean)

Additionally, the time frequency analysis shows that low frequency bands, particularly alpha (8-12 Hz) and theta (4-8 Hz), play a role in decoding lexical items and morphosyntactic features. Specifically, the alpha band was associated with decoding Korean nouns and grammatical number, whereas the theta band was associated with decoding English nouns and Korean grammatical tense. The results for decoding nouns are consistent with the results from Correia et al. (2015), where the frequency band below 12 Hz was found to affect decoding English and Dutch nouns. Also note that the time windows where filtering significantly impacted the decoding accuracy overlap with those where significantly high decoding accuracies were obtained when trained and tested with unfiltered epochs (roughly between 100-500 ms). Intriguingly, however, the current results also show discrepancies in the particular frequency band crucial for decoding nouns in the two languages. Similarly, decoding

Korean number and tense involve different frequency bands – alpha and theta, respectively, while decoding English morphosyntactic features is not found to be associated with either frequency bands. These two frequency bands may be engaged with different cognitive processes, as theta band is often accounted for in terms of lexical retrieval from long-term memory (e.g., Bastiaansen et al., 2005) in contrast to alpha band that is related to sensory processing (e.g., Bastiaansen & Brunia, 2001; Foxe et al., 1998) and cognitive load (e.g., Klimesch et al., 2003). Yet, the exact nature of the relation between each frequency band and neural decoding of different language and grammatical feature is unclear; this warrants further research.

Cross-linguistic neural decoding did not yield above-chance accuracies for either lexical concepts or morphosyntactic features. The at-chance decoding accuracy for cross-linguistic lexical concepts contrasts to previous behavioral studies (Cho and Brennan, 2022; Kim and Davis, 2003) that report robust lexical priming effects between English and Korean. Such difference may indicate that while translation equivalents in two different languages share some conceptual representations, these shared representations are not to the extent for a classifier to learn patterns from for successful decoding from scalp EEG. Also note that although Correia et al. (2015) report above-chance decoding accuracy of animal nouns between English and Dutch between 550 and 600 ms, and between 850 and 900 ms, the classification accuracy itself was low (0.511 vs 0.5 chance accuracy). The fact that English and Korean are linguistically more distant from each other (e.g., different writing systems and language families) compared to English and Dutch might also have contributed to at-chance decoding accuracies in the current study.

Regarding morphosyntactic features, within-language neural decoding already exhibited cross-linguistic differences, such that decoding of English number does not yield above-chance accuracies in the first place, and decoding of tense occurs at different times for the two languages. Results from temporal generalization show that even when trained and tested across different times, accuracies remain at-chance, which indicates that those grammatical concepts may be processed via distinct neural representations in the two languages.

In conclusion, the current study investigated the neural representations of lexical concepts and morphosyntactic features in Korean-English bilinguals by using MVPA. The results show that neural decoding of lexical concepts and morphosyntactic features achieves above-chance accuracies within the same language, with a significant role of theta and alpha oscillations. On the other hand, there is no discernible evidence of above-chance accuracy for between-languages neural decoding, suggesting distinct neural representations of lexical concepts and morphosyntactic features for two different languages.

References

Bastiaansen, M. C. M., Linden, M. van der, Keurs, M. ter, Dijkstra, T., & Hagoort, P. (2005). Theta Responses Are Involved in Lexical—Semantic Retrieval during Language Processing. *Journal of Cognitive Neuroscience*, *17*(3), 530–541. https://doi.org/10.1162/0898929053279469

Bastiaansen, M. C., & Brunia, C. H. (2001). Anticipatory attention: an event-related desynchronization approach. *International Journal of Psychophysiology*, *43*(1), 91-107. https://doi.org/10.1016/S0167-8760(01)00181-7

Boylan, C., Trueswell, J. C., & Thompson-Schill, S. L. (2014). Multi-voxel pattern analysis of noun and verb differences in ventral temporal cortex. *Brain and Language*, *137*, 40–49. https://doi.org/10.1016/j.bandl.2014.07.009

Buchweitz, A., Shinkareva, S. V., Mason, R. A., Mitchell, T. M., & Just, M. A. (2012).Identifying bilingual semantic neural representations across languages. *Brain and Language*, *120*(3), 282–289. https://doi.org/10.1016/j.bandl.2011.09.003

Carlson, T. A., Schrater, P., & He, S. (2003). Patterns of activity in the categorical representations of objects. *Journal of Cognitive Neuroscience*, *15*(5), 704–717. https://doi.org/10.1162/jocn.2003.15.5.704

Chee, M. W. L., Weekes, B., Lee, K. M., Soon, C. S., Schreiber, A., Hoon, J. J., & Chee, M. (2000). Overlap and dissociation of semantic processing of Chinese characters, English words, and pictures: Evidence from fMRI. *NeuroImage*, *12*(4), 392–403. https://doi.org/10.1006/nimg.2000.0631

Cho, J. & Brennan, J. R. (2021). Meaning, but not morphosyntactic features, is cross-linguistically mask-primed in sentential contexts [Conference presentation]. The 34th Annual CUNY Conference on Human Sentence Processing, Philadelphia, Pennsylvania, United States.

Correia, J., Formisano, E., Valente, G., Hausfeld, L., Jansma, B., & Bonte, M. (2014). Brain based translation: fMRI decoding of spoken words in bilinguals reveals language-independent semantic representations in anterior temporal lobe. *The Journal of Neurosci ence*, *34*(1), 332–338. https://doi.org/10.1523/JNEUROSCI.1302-13.2014

Correia, J. M., Jansma, B., Hausfeld, L., Kikkert, S., & Bonte, M. (2015). EEG decoding of spoken words in bilingual listeners: From words to language invariant semantic-conceptual representations. *Frontiers in Psychology*, *6*(FEB), 1–10. https://doi.org/10.3389/fpsyg.2015.00071

Cox, D., & Savoy, R. (2003). fMRI Brain Reading: detecting and classifying distributed pat terns of fMRI activity in human visual cortex. *NeuroImage*, *19*(2), 261–270. https://doi.org/10.1016/S1053-8119(03)00049-1

Datta, S., & Boulgouris, N. V. (2021). Recognition of grammatical class of imagined words from EEG signals using convolutional neural network. *Neurocomputing*, *465*, 301–309. https://doi.org/10.1016/j.neucom.2021.08.035

Foxe, J. J., Simpson, G. V., & Ahlfors, S. P. (1998). Parieto-occipital~ 1 0Hz activity reflects anticipatory state of visual attention mechanisms. *Neuroreport*, *9*(17), 3929-3933.

Gollan, T. H., Forster, K. I., & Frost, R. (1997). Translation priming with different scripts: Masked priming with cognates and noncognates in Hebrew-English bilinguals. *Journal of Experimental Psychology: Learning Memory and Cognition*, *23*(5), 1122–1139. https://doi.org/10.1037/0278-7393.23.5.1122

Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., & Hämäläinen, M. S. (2013) MEG and EEG data analysis with MNE-Python. *Frontiers in Neuroscience*, 7(267), 1-13. https://doi:10.3389/fnins.2013.00267.

Hartsuiker, R. J., Beerts, S., Loncke, M., Desmet, T., & Bernolet, S. (2016). Cross-linguistic structural priming in multilinguals: Further evidence for shared syntax. *Journal of Memory and Language*, *90*, 14–30. https://doi.org/10.1016/j.jml.2016.03.003

Hartsuiker, R. J., & Bernolet, S. (2017). The development of shared syntax in second language learning. *Bilingualism: Language and Cognition*, *20*(2), 219–234. https://doi.org/10.1017/S1366728915000164

Hartsuiker, R. J., Pickering, M. J., & Veltkamp, E. (2004). Is syntax separate or shared between languages? Cross-linguistic syntactic priming in Spanish-English bilinguals. *Psychological Science*, *15*(6), 409–414. https://doi.org/10.1111/j.0956- 7976.2004.00693.x

Hauk, O., Davis, M. H., Ford, M., Pulvermüller, F., & Marslen-Wilson, W. D. (2006). The time course of visual word recognition as revealed by linear regression analysis of ERP data. *Neuroimage*, *30*(4), 1383-1400.

Hoshino, N., Midgley, K. J., Holcomb, P. J., & Grainger, J. (2010). An ERP investigation of masked cross-script translation priming. *Brain Research*, *1344*, 159–172. https://doi.org/10.1016/j.brainres.2010.05.005

Jiang, N. (1999). Testing processing explanations for the asymmetry in masked cross-language priming. *Bilingualism: Language and Cognition*, *2*(1), 59–75. https://doi.org/10.1017/s1366728999000152

Kantola, L., & Van Gompel, R. P. G. (2011). Between-and within-language priming is the same: Evidence for shared bilingual syntactic representations. *Memory and Cognition*, *39*(2), 276–290. https://doi.org/10.3758/s13421-010-0016-5

King, J.-R., & Dehaene, S. (2014). Characterizing the dynamics of mental representations: The temporal generalization method. *Trends in Cognitive Sciences*, *18*(4), 203–210. https://doi.org/10.1016/j.tics.2014.01.002

Klimesch, W., & Schack, B. (2003). Activation of long-term memory by alpha oscillations in a working-memory task? *Behavioral and Brain Sciences*, *26*(6), 743. https://doi.org/10.1017 /S0140525X03370165

Lam, N. H. L., Schoffelen, J.-M., Uddén, J., Hultén, A., & Hagoort, P. (2016). Neural activity during sentence processing as reflected in theta, alpha, beta, and gamma oscillations. *NeuroImage*, *142*, 43–54. https://doi.org/10.1016/j.neuroimage.2016.03.007

Lee-Ellis, S. (2009). The development and validation of a Korean C-Test using Rasch analysis. *Language Testing*, *26*(2), 245–274. https://doi.org/10.1177/0265532208101007

Mitchell, T. M., Shinkareva, S. V., Carlson, A., Chang, K. M., Malave, V. L., Mason, R. A., & Just, M. A. (2008). Predicting human brain activity associated with the meanings of nouns. *Science*, *320*(5880), 1191–1195. https://doi.org/10.1126/science.1152876

Momsen, J. P., & Abel, A. D. (2022). Neural Oscillations Reflect Meaning Identification for Novel Words in Context. *Neurobiology of Language*, *3*(1), 132–148. https://doi.org/10.1162/nol_a_00052

Peirce, J. W., Gray, J. R., Simpson, S., MacAskill, M. R., Höchenberger, R., Sogo, H., Kast man, E., Lindeløv, J. (2019). PsychoPy2: experiments in behavior made easy. *Behavior Research Methods.* https://doi.org/10.3758/s13428-018-01193-y

Pulvermüller, F., Lutzenberger, W., & Birbaumer, N. (1995). Electrocortical distinction of vocabulary types. *Electroencephalography and clinical Neurophysiology*, *94*(5), 357-370.

Rivet, B., Souloumiac, A., Attina, V., & Gibert, G. (2009). xDAWN algorithm to enhance evoked potentials: application to brain–computer interface. *IEEE Transactions on Biomedical Engineering*, *56*(8), 2035-2043.

Shin, J. A., & Christianson, K. (2009). Syntactic processing in Korean-English bilingual pro duction: Evidence from cross-linguistic structural priming. Cognition, *112*(1), 175–180. https://doi.org/10.1016/j.cognition.2009.03.011

Shinkareva, S. V., Malave, V. L., Mason, R. A., Mitchell, T. M., & Just, M. A. (2011). Commonality of neural representations of words and pictures. *NeuroImage*, *54*(3), 2418–2425. https://doi.org/10.1016/j.neuroimage.2010.10.042

Simanova, I., van Gerven, M., Oostenveld, R., & Hagoort, P. (2010). Identifying object cate gories from event-related EEG: Toward decoding of conceptual representations. *PLoS ONE*, *5*(12), e11465. https://doi.org/10.1371/journal.pone.0014465

Yudes, C., Domínguez, A., Cuetos, F., & De Vega, M. (2016). The time-course of processing of grammatical class and semantic attributes of words: Dissociation by means of ERP. *Psicológica*, *37*(2), 105-126.

Xue, G., Dong, Q., Jin, Z., Zhang, L., & Wang, Y. (2004). An fMRI study with semantic ac cess in low proficiency second language learners. *NeuroReport*, *15*(5), 791–796. https://doi.org/10.1097/00001756-200404090-00010

Zinszer, B. D., Anderson, A. J., Kang, O., Wheatley, T., & Raizada, R. D. S. (2015). You say potato, I say tǔdòu: How speakers of different languages share the same concept. In D. C. Noelle, R. Dale, A. S. Warlaumont, J. Yoshimi, T.

Matlock, C.D. Jennings, & P. P. Maglio (Eds.), *Proceedings of the 37th Annual Meeting of the Cognitive Science Society* (pp. 2829-2834). Austin, TX: Cognitive Science Society.

Zinszer, B. D., Anderson, A. J., Kang, O., Wheatley, T., & Raizada, R. D. S. (2016). Seman tic structural alignment of neural representational spaces enables translation between English and Chinese words. *Journal of Cognitive Neuroscience*, *28*(11), 1749–1759. https://doi.org/10.1162/jocn