Semantics across the globe: A universal neurocognitive semantic structure adaptive to climate

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Abstract

Thousands of languages are used worldwide as the primary means of human thought and communication. While both similarities and variations in word meaning (semantics) across different languages are well recognized, the underlying mechanisms remain enigmatic without a coherent theoretical model for semantic representation. Given that semantic representation is a product of the human brain, we address this issue through the lens of the neurocognitive theories, with the consensus framework that semantics are derived from sensory experiences, with a set of sensory and cognitive dimensions being identified as biologically salient in neuroscientific studies. We operationalized word semantic representations with this set of specific dimensions, using computation models (53 languages' word embedding data; Study 1), human behavioural ratings (253 subjects, 8 languages; Study 2), and brain activity data (86 subjects, 45 languages; Study 3), and analyzed the similarity and variation patterns of concepts across different languages. These three approaches converge on finding that, across diverse language samples, word semantic representations along the neurocognitive dimensional structures exhibit strong commonalities, with variations along this structure being significantly and uniquely explained by climate, beyond sociocultural-centered variables. These results present a universal biologically constrained semantic structure that is adaptive to environmental inputs, reconciling the classical universality and relativity debate.

Keywords: Word meaning; Universal semantics; Cross language alignment; Climate.

Main

There are currently over 7,000 spoken and signed languages worldwide, each with distinct sound and visual forms and syntactic rules. Do speakers of different languages simply use different word forms to map onto a common conceptual structure, i.e., do people speaking “rose” and “玫瑰” have the same semantic representation? If not, what is lost in translation? This question is part of the classic debate on language universality versus relativity of whether speaking different languages is associated with different cognitions more broadly (Wierzbicka, 1992b; Kay & Kempton, 1984; Majid et al., 2004). It seems trivial that both commonalities and variations exist — most languages have words referring to phenomena such as the sun or the color red, while the words for the object “rose” entail notions of romance in some languages but not in others. The key question is what principles underlie these commonalities and variations across languages. Answers to this question not only address semantic representation principles but also provide a foundation for better communication across languages and cultures.

Universality and variations documented by large-scale language computation

Rich commonalities and variations have been documented across multiple disciplines, including anthropology and linguistics. Ethnographic descriptions by anthropologists and linguists have revealed common concepts in semantic domains, such as color (Berlin & Kay, 1991) and emotion (Wierzbicka, 1992a; Ekman, 1992). On the other hand, different languages have different words to refer to the same perceptual referents, culturally bound words that are difficult to translate, and different ways of categorizing the world (Majid et al., 2018; Passmore & Jordan, 2020; Majid et al., 2004). Notably, advances in recent large language models allow for word representation computations across huge amounts of natural language use data, facilitating large-scale cross-language comparisons (Thompson et al., 2020; Youn et al., 2016; Lewis et al., 2023; see the review, Jackson et al., 2022). In this approach, word meaning alignment across languages (e.g., *beauty* in English and *bella* in Italian) is assessed by comparing their relationships to a set of other words (*anchor words*) in high-dimensional representation spaces. Different studies have used various types of *anchor words* (i.e., different model spaces), including domain-specific words (e.g., the concept “dust” is represented by other natural phenomena words), neighboring words, or all words, each implicitly driven by different assumptions about word semantic representation. Different results and conclusions have been reached accordingly, supporting either word semantics being “innate” (Youn et al., 2016) or culturally driven (Thompson et al., 2020; Lewis et al., 2023). It is difficult to evaluate whether these differences reflect that certain aspects of word meaning (approximated by *anchor words*) are more universal than others across experiments, given the differences in stimuli and computational methods. To this end, what has been missing is an overarching theoretical framework: What aspects (underlying dimensions) of human semantic mechanisms are hypothesized to be universal? How do variations arise from this universal mechanism?

A candidate model: Neurocognitive framework of semantic representation

We propose that a strong candidate framework is the intrinsic way in which the human brain represents semantic knowledge. The biological constraints of the human brain are the result of the biological evolution of *homo sapiens* and lay the foundation for universality (see similar arguments for color space in Berlin & Kay, 1991; emotion space in Jackson et al., 2019), and phenomenal variations (at least partly) result from the input information that feeds into such a biological structure. Neurocognitive research reveals a consensus that semantic representation in the brain is derived from sensory and language experiences in ways respecting the specific information processing architectures of the brain: Brain responses to word meanings are distributed along sensorimotor and related associative cortical networks, respecting domains of evolutionary saliency, with activity strength modulated by the meaning's loading on corresponding attributes/domains (Martin et al., 1995; He et al., 2013; Fernandino et al., 2016; Fernandino et al., 2022). Lesions in the brain lead to deficits along the lines of these sensory-motor modalities and domains (Capitani et al., 2003; Miceli et al., 2001; Buxbaum et al., 2000). Some aspects of the neural organization are present early in human infancy (Deen et al., 2017; Wen et al., 2022), have been found across diverse cultures and languages (e.g., US, UK, Italy, and China), even in individuals with drastic experiential differences such as complete visual deprivation (Bottini et al., 2020; X. Wang et al., 2020; Bi, 2021; Mahon & Caramazza, 2011). These empirical findings have led to several mainstream neuroanatomical semantic models, which all agree that word semantics are (at least partly) grounded in our world knowledge, including: GRAPES (Grounding Representations in Action, Perception, and Emotion Systems; Martin, 2016); Embodied Abstraction (Binder et al., 2016; Binder & Desai, 2011); Hub-and-Spoke Model (Lambon-Ralph et al., 2017; Patterson et al., 2007); and Neural Dual Coding Theory (Bi, 2021). All theories assume it being a universal biological structure for semantics, but the commonalities and variations along this framework have not been systematically tested across a large number of languages.

We extend this neurocognitive framework of semantic representations, i.e., representing word semantics along the core neurocognitive dimensions, to investigate its effectiveness in explaining semantic commonalities and variations across languages. To operationalize, we gleaned 13 (primitive) dimensions that have extensive evidence for their neural correlates, and constructed word semantic representation composed of these 13 dimensions (Binder et al., 2016; see Table S1 for example studies and evidence): sensorimotor dimensions of the human brain system (*color*, *shape*, *taste*, *smell*, *sound*, *touch*, and *bodily motor*) and core cognitive domains (*time*, *space*, *number*, *mental-cognition*, *emotion*, and *social*). Word representations as 13-dimensional vectors will be tested across languages: how similar are the words for 'rose' in different languages in terms of their loading (relation) patterns with *color* (e.g., red, blue), *shape* (e.g., round, square), *emotion* (e.g., happy, sad, anger), etc.?

Predictions of the neurocognitive framework of semantic representation

The neurocognitive framework of semantic representation intrinsically makes the following predictions regarding commonalities and variations (Figure 1).

First, semantic representation derived from this neurocognitive framework better captures the "universal structure" of semantic representations compared to other models (Figure 2a), including distributional semantic models (Thompson et al., 2020), psycholinguistic semantic featural models (Buchanan et al., 2019; McRae et al., 2005), and randomized statistical control models. These alternative models are prevalent in cognitive disciplines without explicit considerations of the neurobiological basis and have been shown to be less correlated with word semantic brain activities than the neurocognitive dimensional model (Fernandino et al., 2022).

Second, regarding variations along this dimensional structure, the intrinsic assumption of the framework that semantic representation derives from sensory (and language) channels predicts that variability is the natural consequence of variables affecting these channeled experiences, including those associated with both natural and cultural environments (Kemmerer, 2023). This perspective differs from those of previous studies that predominantly emphasized sociocultural factors, including geographic distance (Jackson et al., 2019), communication pressures (Zaslavsky et al., 2020), linguistic history (Jonauskaite et al., 2020), and cultural proximities (Thompson et al., 2020). These variables were mainly motivated by the significance of communication, word borrowing, and phylogenetic history in the cultural evolutionary process for cross-language alignment (Jackson et al., 2019; Lindquist et al., 2022). However, it is possible that languages used in distant locations share similar conceptual meanings when they have comparable sensory signals and similar neurocognitive structures. One salient ecological variable worth highlighting is climate, which has been shown to be strongly associated with natural and cultural properties (Bentz et al., 2018; Van de Vliert, 2020; Wormley et al., 2023). By systematically considering these macroscale environmental variables, we predict that climate, as an ecological factor shaping sensory environments, exerts independent effects on human semantic processes beyond previously tested sociocultural-centered variables (geographic, linguistic, and cultural distance).

<u>Study overview</u>

We conducted a series of studies to test the above predictions about cross-language alignment patterns through multiple approaches – computational, behavioral, and neural measures – for convergence (Figure 1). Study 1 involved language computational analyses on large-scale multilingual pretrained word-embedding data (Grave et al., 2018). For the universality prediction, we compared the extent of commonalities captured by the target model (with the 13 neurocognitive dimensions as *anchor words*) and alternative models (different types of *anchor words*). For the variation prediction, we examined the relationship between variations along this neurocognitive dimensional structure and ecological variables across languages. Such models have the advantage of analyzing large scale language patterns, but the relationship of ecological variables with the human mind/brain is approached indirectly through computational relationships. Thus, in Study 2, we collected human individual semantic behavioral ratings on these 13 dimensions, and in Study 3, analyzed brain activity patterns during language comprehension, linking cognition and biology variations more directly with the ecological variables of interest. Figure 1 (bottom panel) illustrates the geographic distribution of language samples across three studies, with detailed language information provided in Table S2.

Results

<u>Commonalities on the neurocognitive semantic structure</u>

<u>Study 1a. Language model study using word embedding data in 53 languages (commonality)</u>

We focused on the NorthEuralex (NEL) wordlist, which provided translational equivalent 1,016 concepts across 107 languages. Among them, 53 languages (spanning 10 language families) were well covered in the recently developed large language model databases (fastText multilingual word vectors; Grave et al., 2018). These databases provided 300-(hidden)-dimensional word embedding vectors for a large number of languages, pretrained on vast corpora comprising billions of words for each language. For each target concept in each language, we projected its embedding onto different sets of anchor words based on different models (see below), i.e., computing the target-anchors cosine distances (see an illustration of construction processes in Figure 2a; see also the "semantic projection" method in Grand et al., 2022; Lewis et al., 2019; Chersoni et al., 2021). Distances to different model-driven anchor sets were taken as the model-based semantic representations for the target concepts, based on which cross-language comparisons were performed.

Constructing different model-anchor-based semantic representations from word embedding data.

Distributional semantic models. A prevalent approach in cross-language semantic comparisons represents concepts by their usage contexts (Thompson et al., 2020). Following this approach, we represented the 1,016 concepts using their local patterns (i.e., anchor words were semantic neighbors, N = 100) and global patterns (i.e., anchor words were the entire word space).

Semantic feature models. The psycholinguistic tradition employs semantic feature models based on decompositional semantic features, which were derived from human-generated descriptive terms. Following this approach, anchor words were obtained from the feature norms reported in Buchanan et al. (2019), focusing on the 100 feature words with the highest frequency.

Neurocognitive semantic models. Neurocognitive semantic models, like semantic feature models, assume decompositional representation but highlight a set of underlying “primitive” dimensions constrained by the human brain. We identified 13 primary structural dimensions from neurocognitive semantic research (see Introduction and Table S1 for a list of example empirical references). Anchor words corresponding to these dimensions were manually selected from the NEL concept list (see Methods for details; anchor word list shown in Table S3). Concepts were projected onto these 13 neurocognitive salient dimensions by averaging semantic distances of anchor words within each dimension. Our text-derived dimension loadings significantly correlated with the human rating data reported in Binder et al. (2016) (Pearson $r = 0.42$, $P < 1 \times 10^{-16}$; see Figure S1 for details), consistent with previous findings on subjective-rating validity for the dimension computation (Chersoni et al., 2021).

Statistical control models. To assess the explanatory powers of the above candidate theoretical models for the cross-linguistic semantic universality, we further computed two types of theory-free benchmark distributions. One type is random word models, where 100 randomly selected words from the original NEL list served as anchors, and concepts were projected onto these anchors’ embedding vectors, with 10,000 iterations. The other is random dimension models, where 100 randomly selected words were grouped into 13 dimension “anchors” using K-meanings clustering, and concepts were then projected onto these pseudo dimension, with 10,000 iterations. The statistical confidence for each theoretical model’s universality was established by comparing its position with these two models’ distributions.

Commonalities across languages: Better captured by neurocognitive models

We used two methods to assess the universality of our candidate semantic models for convergence: inter-language correlation analysis (Figure 2b) and principal component analysis (PCA; Supplementary Text S1, Figure S2).

Inter-language correlation results. To quantify cross-language similarity, we computed Fisher-Z transformed Pearson R correlation coefficients between model-based semantic representations for each language pair. As shown in Figure 2b (left panel), the neurocognitive-dimensional semantic representation had greater cross-language similarity compared to the other two representation types (mean Fisher-z-transformed r: $M_{\text{neurocognitive}} = 0.63$, $SD = 0.19$; $M_{\text{distributional (global)}} = 0.42$, $SD = 0.17$; $M_{\text{distributional (local)}} = 0.33$, $SD = 0.10$; $M_{\text{semantic feature}} = 0.35$, $SD = 0.13$; neurocognitive vs. distributional (global): Wilcoxon test V = 950123, $P < 1 \times 10^{-16}$; neurocognitive vs. distributed (local): Wilcoxon test V = 950131, $P < 1 \times 10^{-16}$; neurocognitive vs. semantic feature: Wilcoxon test V = 750925, $P < 1 \times 10^{-16}$). These results were robust when we varied the number of anchor words in the distributional (local) and feature models (see Figure S3). Figure 2b (right panel) illustrates that the mean inter-language correlation of neurocognitive models (depicted by red vertical line) exceeded the upper ends of distributions of random word models (depicted by light gray area; P < 0.0001) and random dimension models (depicted by dark gray area; P = 0.005), whereas the other types of theoretical models did not demonstrate this pattern.

Principal component analysis results. We also employed a complementary PCA on 204 concepts common to all 53 languages, treating languages as "features" and semantic patterns as "samples". This approach assumes that a universal semantic structure would manifest as a relatively high first component (PC1), with the variance explained by PC1 reflecting the degree of universality (Cole et al., 2014; Romney et al., 2000). The neurocognitive-dimensional representation of concepts again has a greater amount of universality (neurocognitive: 44.31%; global-distributed: 34.16%; local-distributed: 36.38%; feature-based: 34.45%). Similar to the inter-language correlation findings, in comparison with statistical random models, the neurocognitive model, not the other two, was positioned at the upper bounds of their distributions, signifying a relatively universal semantic structure (P < 0.0001 and P = 0.01, respectively). Detailed results, including the scree plot and neurocognitive structure PC1 matrix, are presented in Supplementary Text S1 and Figure S2.

We further validated the main analyses above using text embedding data derived from different corpora (Supplementary Text S2, Figure S4).

Generalization to colexification networks with 2681 languages

To test the generalizability of neurocognitive semantic structures beyond these initial 53 languages, we investigated whether the neurocognitive semantic model could predict word relational patterns in a larger, more diverse language sample. Given the challenges of obtaining semantic representations for low-resource languages, we utilized the database of Cross-Linguistic Colexifications (CLICS), which contains colexification patterns from 2,681 languages (Rzymski et al., 2020). We employed common topological network metrics, including edge, common neighbors, and two community-based measures (Louvain and Infomap algorithms), and used the average distance across these four metrics as the word distance in the topological graph space. The hypothesis here is that if the neurocognitive semantic model outperforms statistical control models in predicting word topological patterns in the colexification network, it would indicate the generalizability of these structures to a broader range of languages. Specifically, we examined whether concepts closer in the 13-dimensional neurocognitive space derived from the original 53 languages (all Eurasian) embedding data were more likely to be topologically proximate in the colexification network.

We conducted Spearman rank correlations between 165 NEL concepts in the embedding-constructed neurocognitive semantic space and the CLICS topological graph space (Figure 2c, left panel). For statistical comparison, we generated random models (word and dimension) and correlated them with the CLICS graph space 1,000 times to establish null distributions. These tests were performed on the following samples: 1) the entire language sample (N = 2,681) and 2) non-Eurasian languages (South America, North America, Africa, Papunesia, and Australia; N = 1,813, excluding unclassified languages). The second test specifically targeted other language samples that were not included in our initial word embedding analysis.

As shown in Figure 2c (right panel), the neurocognitive dimensional representation derived from the original 53 languages significantly explained topological similarities in the colexification network for both the 2,681 languages and the non-Eurasian subset (both *P*s < 0.01). In both cases, the neurocognitive model's performance was at the upper bound of the random model distributions, providing positive evidence for the cross-linguistic generalizability of these semantic structures. Separate density plots for each non-Eurasian area's language samples yielded similar patterns to the entire sample (Figure S5).

Summary of the commonality analyses results: The 13-neurocognitive-dimensional structure, obtained from brain studies in a few industrialized languages (see Table S1), captures cross-language similarities better than control models in the word embedding spaces of 53 languages, which further generalizes to explaining word similarities across a larger and more diverse set of languages in the CLICS networks (colexification data).

Variations associated with environmental variables

Study 1b – Language model study using word embedding data in 53 languages (variation)

Having established the superiority of the neurocognitive semantic model in capturing semantic universality, we then investigated variations across languages along this "universal structure". Based on the shared assumption of semantic neurocognitive theories that semantic representations are derived from sensorimotor (and language) experiences, we hypothesized that variations in the model stem from variables affecting these channels of experiences, including both natural and cultural environmental factors. The following variables were considered: climate, geographic, linguistic history, and culture variables. The question under scrutiny was whether and how variations across languages along the universal neurocognitive semantic structures could be explained by these external variables (i.e., whether language pairs with similar environmental characteristics exhibit similar semantic representations).

To address this question, we employed representation similarity analysis (RSA; Kriegeskorte et al., 2008) to quantitatively model cross-language variations in semantic representational geometries by regressing the semantic dissimilarity representational matrix (RDM; Figure 3a) on the RDMs of our selected environmental variables. Data on environmental variables for 53 languages were extracted from various official public databases using latitude and longitude provided by Glottolog 4.6 (Hammarström et al., 2022). The sample sizes (i.e., language pairs) varied depending on the availability of the environmental data.

Association between neurocognitive semantic structural variation and environmental variables. Correlation analyses first revealed moderate associations between these four environmental RDMs and the semantic RDM (Spearman ρs = 0.39 – 0.53, *P*s < 1×10^{-16}; Table S4). Within a sample of 29 languages (406 language pairs) where all four environmental variables were available, they collectively explained 28% of the semantic (neurocognitive) space variations (Spearman ρ = 0.53; P < 1×10^{-16}).

We then employed a linear mixed regression model to assess the unique effect of each environmental factor. This approach accounts for potential biases arising from non-independent language sampling by considering a crossed random-effects structure that nested language pairs within language families. As indicated in Figure 3b, climate showed the strongest unique explanatory effects (climate: β = 0.32, 95% CI = [0.22, 0.43], P = 7.04 × 10^{-9}). Cultural, linguistic history and geographic distance did not show significant unique contribution to semantic variations (culture: β = 0.03, 95% CI = [-0.06, 0.12], P = 0.58; linguistic history: β = -0.03, 95% CI = [-0.11, 0.05], P = 0.43; geography: β = 0.09, 95% CI = [-0.008, 0.19], P = 0.07). Further analyses revealed that climate contributed significant effects across 12 of the 13 semantic dimensions (FDR-corrected *q*s < 0.05), with the exception of the shape dimension (q = 0.12; Figure 3c, left panel). The climate effects were robustness across multiple validation analyses, including those utilizing alternative pretrained word-embedding data and methods controlling for non-independence (see Supplementary Text S2, S3; Figure S4; Table S5). While the effects of the other three variables reached statistical significance in some validations, they showed less consistent patterns across analyses.

Mediation analyses. Previous research has demonstrated significant associations between culture and climate, as well as between culture and semantics (Wormley et al., 2023; Thompson et al., 2020). We thus ran multiple linear regression mediation analyses to understand the relation among these three variables. Results (Figure 3c; right panel) showed that climate affects semantics both through culture, and directly (direct effect: β = 0.36, 95% CI = [0.23, 0.48], P < 1 × 10^{-16}; culture mediation effect: β = 0.15, 95% CI = [0.07, 0.24], P < 1 × 10^{-16}). Interestingly, climate has both direct effects on culture and indirect effects through semantics (direct effect: β = 0.65, 95% CI = [0.58, 0.73], P < 1 × 10^{-16}; semantic mediation effect: β = 0.07, 95% CI = [0.03, 0.11], P = 8 × 10^{-4}).

Study 2: Human participants' behavioral ratings in 8 languages

To investigate whether the principles of commonalities and variations observed in language records (Study 1) are reflected in language speakers' semantic behaviors, we conducted a study with participants from 8 languages (a subset of 53 languages in Study 1) with a broad coverage of geographic, linguistic, and cultural diversity: Arabic (Egypt), Chinese (China), English (USA), Hindi (India), Japanese (Japan), Korean (South Korea), Russian (Russia), and Spanish (Spain). We recruited a final sample of 253 participants from 58 city sites across these countries (sampling procedures and geographical information are provided in Methods, Figure S6 and Table S6). Participants were asked to rate the Swadesh concepts (N = 207, Table S7) on their associations with the 13 neurocognitive dimensions, resulting in individual semantic spaces comprising 2,691 ratings per participant (207 Swadesh concepts × 13 neurocognitive dimensions). We computed Pearson correlations between the rating vectors (207 concepts × 13 dimensions) for each participant pair, resulting in an *intersubject correlational matrix* (Figure 3d). The matrix showed a substantial semantic component shared across participants (65.78%), with much smaller language-specific effects (4.2%), validating the commonality of such neurocognitive semantic structures across languages (see Supplementary Text S4 for details).

Behavioral variations associated with climate and cultural distances. To assess the relationship between neurocognitive semantic space variation and environmental variables, we collected macroenvironment variables (identical to those in Study 1) for individuals and visualized them as inter-subject environmental RDMs in Figure 3e. We also included a demographic RDM to account for variations in participants' age, gender, education level, and socioeconomic status.

Correlation analyses first revealed significant associations between the four environmental RDMs and the semantic RDM (Spearman *ρ*s = 0.02 – 0.25, *P*s < 0.001; Table S8). We turned these RDMs into ranked data and performed linear regression models to obtain the explanatory effects of each variable on semantics. Hierarchical regression revealed that, in addition to the explanatory power of demographic distance ($R^2 = 0.01$), the four environmental variables collectively accounted for an incremental 7.1% variance in the neurocognitive semantic structural variations (Spearman $\rho = 0.27$, $P < 1 \times 10^{-16}$). Then, we ran a linear mixed model with a crossed random-effects structure that nested subject pairs within language families to consider non-independent sampling. Beta estimation (Figure 3e) showed that both climate and culture had unique effects on cross-language semantic variation (climate: $\beta = 0.12$, 95% CI = [0.11, 0.13], $P < 1 \times 10^{-16}$; culture: $\beta = 0.13$, 95% CI = [0.12, 0.14], $P < 1 \times 10^{-16}$). Geography and linguistic history showed no or negative effects (geography: $\beta = -0.01$, 95% CI = [-0.01, 0.007], P = 0.53; linguistic history: $\beta = -0.02$, 95% CI = [-0.03, -0.01]). The results remained robust when using other methods to control for non-independence, see Supplementary Text S3 and Table S9). When analyzing each neurocognitive dimension separately (Figure 3f, left panel), all dimension variations continued to be significantly modulated by climate and culture (FDR-corrected qs < 0.05).

Mediation analyses. We observe associations between semantic variations and both climate and cultural variables. We thus ran mediation linear regressions for the relation among these three variables. Results (Figure 3f, right panel) showed that climate affects semantics both through culture and directly (direct effect: $\beta = 0.20$, 95% CI = [0.19, 0.22], $P < 1 \times 10^{-16}$; culture mediation effect: $\beta = 0.04$, 95% CI = [0.03, 0.05], $P < 1 \times 10^{-16}$). Climate has both direct effects on culture and through semantics (direct effect: $\beta = 0.58$, 95% CI = [0.575, 0.59], $P < 1 \times 10^{-16}$; semantic mediation effect: $\beta = 0.01$, 95% CI = [0.009, 0.01], $P < 1 \times 10^{-16}$).

Study 3: Human participants' brain activity patterns in 45 languages

To investigate whether the principles of commonalities and variations observed in language records (Study 1) are reflected in language speakers' neural responses during language comprehension, we analyzed a multi-language functional magnetic resonance imaging (fMRI) dataset comprising 86 individuals recruited from the United States, whose native languages spanned across 45 languages across 12 language families (Malik-Moraleda et al., 2022). We focused on neural activity during native language processing, specifically examining the contrast between intact and acoustically degraded language conditions in the 12 language-responsive regions (6 left, 6 right) in the language network (Figure 4a; Fedorenko et al., 2010).

Neural variations associated with cross-language semantic alignments. We first investigated whether subjects' neural activity patterns in these regions reflected cross-language alignment in the 13-neurocognitive-dimensional semantic space, based on the language model computational results in Study 1 (Figure 3a). To this end, for overlapping language samples in two studies (65 participants, 33 languages; Figure 4b), we computed inter-subject neural RDMs from individual t-value maps in each brain region, and then correlated these neural RDMs with inter-subject neurocognitive semantic model RDM (based on each subject's language). Significant associations were found in bilateral anterior temporal lobes (ATLs) and the left angular gyrus (Spearman ρ = 0.06 - 0.20, FDR-corrected qs < 0.05). That is, the more closely aligned two languages are for the 13-neurocognitive dimensional semantic representation, the more similar their speakers' brain activities are in these brain regions. We conducted the following analyses on these regions of interest (Figure 4c). We first found that these regions shared certain degree of cross-language commonalities, validating our commonality results (Supplementary Text S4).

Neural variations associated with climate and cultural distances. To assess the relationship between neural activities in these brain regions-of-interest and environmental variables, we obtained macroenvironment variables from official public databases used in Study 1 and constructed inter-subject environmental RDMs based on their native languages' coordinates (Figure 4d). We analyzed a subset of data including 49 participants across 25 languages for which all environmental distance measures were available. We constructed linear mixed models: first a model incorporating geographic distance and linguistic family as phylogenetic controls, and a model of interest that additionally included climate and cultural distances. Both models incorporated random intercepts for each participant dyad to account for data non-independence, following recent practice in analyzing inter-subject neural data (Chen et al., 2017). Greater fitness of the second model in comparison to the first would indicate significant effects of climate and culture distances in explaining neural RDMs. Results showed that neural activity pattern similarities across speakers in bilateral ATLs, not the left AG, were significantly predicted by climate and cultural factors (left ATL: $\Delta AIC = -11.62$, $P < 0.001$; right ATL: $\Delta AIC = -10.68$, $P < 0.001$; left AG: $\Delta AIC = -1.83$, $P = 0.054$). Specifically, as shown in Figure 4e, climate had significant effects in the right ATL ($\beta = 0.11$, $P = 0.002$), while cultural factors in the left ATL ($\beta = 0.10$, $P < 0.001$).

<u>Summary of the variation analyses results</u>: Cross-language variations on the 13-neurocognitive-dimension structure obtained from language computation data (Study 1), human behavior rating data (Study 2), and multi-language fMRI data (Study 3), were all significantly predicted by climate, the effects of which were also robust across all validation analyses. Study 2 and 3 also revealed effects of cultural variations. Climate and cultural effects were found to be associated with neural activities in different brain regions (climate: the r-ATL; cultural: the l-ATL).

Exploratory analyses on the associative patterns between climate and semantic space

Having identified that climate has robust and unique effects on variations in semantic structures across large text models (Study 1b), subjective ratings (Study 2), and brain activity patterns (Study 3), we aimed to elucidate the semantic profiles that are associated with the major climate groups. We carried out the following analyses based on the embedding data from Study 1 given that this study covers the largest language samples and concept set. We performed a PCA on climate data consisting of 19 biologically relevant climate variables related to temperature and precipitation across 53 languages. The results revealed two primary climate-related principal components (PCs): Climate-PC1, accounting for 42.3% of the variation, and Climate-PC2, accounting for 30% (Figure 5a). The contributions of specific climate variables to these PCs (Table S10) led us to characterize Climate PC1 as representing "cold/temperate vs. tropical" climates and Climate PC2 as representing "oceanic vs. continental" climates (more precipitation and low seasonality vs. less precipitation and high seasonality).

To project the semantic space along each PC axis, we scaled the semantic space for each language and multiplied it by their loadings on the two climate PCs, resulting in semantic spaces along the Climate PC1 and Climate PC2 axes (Figure 5b). Higher values along a particular direction of PCs indicate that the given climate type tends to have stronger semantic relations. The associated semantic space for Climate PC1 and Climate PC2 is visualized for each concept (Figure S7) and summarized by domains (Figure 5b). For Climate PC1 (cold/temperate vs. tropical) dichotomy, concepts in general tend to exhibit higher intensity on emotional and sensorimotor dimensions (touch, motor, shape, color) in the cold/temperate zones and higher intensity on social-cognitive (social, space, number, cognition) and smell dimensions in tropical zones. For Climate PC2 (oceanic vs. continental) dichotomy, concepts tend to exhibit higher intensity on the smell, cognition, and time dimensions in the oceanic zone and higher intensity on the social and sound dimensions in the continental zone.

One data pattern emerged from this visualization (Figure 5b): The dimensional difference patterns associated with climate groups are overall coherent across various concepts (and concept domains). For Climate PC1, cold/temperate climate is associated with higher loading on emotion (and sensorimotor) not only for specific concepts relating to temperature, such as “sun” or “warm”, and tropical climate is associated with higher loading on olfactory not only for “flower” and on social not only for “father”, but for all domains of concepts in general. This pattern of association with dimensions instead of concept domains is also present for Climate PC2, although less clear-cut (see examples in Figure 5b, lower panel).

Discussion

Research on how the human brain processes semantics, using a handful of commonly studied languages (e.g., English, Italian, Chinese), has revealed semantic representation along a set of neurocognitive-related salient dimensions. We tested the commonalities and variations along this neurocognitive structure across different languages using multiple approaches, including language computation models, human subjective behavioral ratings, and multi-language fMRI data (see summary in Figure 1). Two key results were obtained. First, across 53 languages, representation on the neurocognitive semantic model had greater similarity than on alternative semantic models (distributional semantic models and semantic feature models) and statistical control models. The shared neurocognitive representation of the 53 languages significantly predicted the colexification network relations across 2,681 languages. Second, variation patterns were accommodated by the intrinsic assumptions of the neurocognitive semantic model: the variations along such structures in terms of language embedding computation, human subjective semantic rating, and neural activity patterns during language comprehension, were all significantly predicted by major macro-environmental factors, with variables strongly affecting the sensory inputs – climate – having the most robust effects beyond those of linguistic and cultural factors. Below, we discuss these key findings in turn.

<u>Stronger universality of neurocognitive model compared to control models.</u>

Previous studies on cross-language semantic alignments have focused on the degree of the alignments on concepts – with how much fidelity a word translates across languages (colexification; used within similar relations). Take the word “rose” as an example: to what degree can words referring to the concept “rose” in different languages be translated accurately back and forth (colexification) or be related to similar words? Both universality (Youn et al., 2016) and variations (Thompson et al., 2020; Lewis et al., 2023) have been highlighted. Aligning with the significant universality observations, we observed that there are substantial similarities across languages above chance in semantic representations constructed from all models, including the neurocognitive dimensional (both computed and subjectively rated), full distribution (local and global), and psycholinguistic semantic feature models.

Critically, the current study moves beyond magnitude analyses and tests predictions about the nature of the potential universal semantic structure – What aspects of the meaning of “rose” are more similar? We reasoned that a promising candidate for a universal semantic structure that is coherent with how semantics are processed in the human brain – the neurocognitive semantic structure – consists of: sensory-motor dimensions (*color*, *shape*, *sound*, *touch*, *taste*, *smell*, *bodily motor*) and core cognitive dimensions/domains (*time*, *space*, *number*, *mental-cognition*, *emotion*, *social*). For instance, words referring to objects containing rich color information, such as “rose” activate color perception areas (e.g., lingual/fusiform gyrus) more strongly than those that do not (e.g., “kick”), and the neural activity pattern in the corresponding brain region reflects color perceptual space such that the neural activity to the word “banana” would be closer to “corn” than to “strawberry” (US data, Martin et al., 1995; Italian data, Bottini et al., 2020; Chinese data, X. Wang et al., 2020). These neurocognitive dimensions, gleaned from neuroimaging studies based on a few languages (see Table S1), capture similarities across much larger language samples (53 languages, spanning 10 language families including Indo-European, Afro-Asiatic, and Dravidian), most of which have not been studied in cognitive neuroscience (e.g., Breton, Bashkir, and Tatar). Importantly, the cross-language similarity for word semantic representations computed this way is significantly greater than those computed based on its relational structures with global or local neighboring words, or with psycholinguistic features that were not as neurobiologically salient. The advantage of the neurocognitive model over these control models on the same dataset is not readily explained by some potential limitations of the language samples (e.g., all Eurasia). Further confidence is gained from the results showing that the shared neurocognitive representation of the 53 languages significantly predicts colexification network properties across 2,681 languages. These results are readily explained by the assumption that these neurobiological structures scaffold a universal semantic representation regardless of the types of languages spoken.

Variations along the neurocognitive semantic structure associate with climate

Regarding variations, aligning with the observations of the cultural/linguistic effects on concept-level alignment (Thompson et al., 2020; Lewis et al., 2023), we found that deviations along the neurocognitive dimensional structures were significantly associated with cultural similarity in Study 2 and 3, suggesting that sociocultural processes (via word borrowing, cultural communications) could also help promote alignment on such semantic structure. The key novel finding is the robust unique effect of climate beyond these variables in explaining semantic variations across the language computation model, individual human behavior, and brain data.

Given the universal neural mechanism of deriving semantic representation from multimodal sensorimotor experiences (respecting core knowledge domains), environmental variables could have an effect on sensory experiences and/or related bodily functions, which in turn would affect semantic representations. Climate is one such variable. Indeed, climate properties such as temperature and precipitation contribute to human perceptual environments such as sun color, landscape variations, and interaction patterns among local populations, plants, and animals. Recent evidence has even suggested that oxygen concentration and/or other environmental factors associated with high altitude affect color perception, which is assumed to be driven by different oxygen consumption sensitivities of different cones in the retina (Kobrick, 1970; Z.-X. Wang et al., 2019). Speakers who reside in distant locations but experience similar climates are more likely to share similar sensory/perceptual inputs and thus more similar semantic representations. Notably, the impact of climate goes beyond sensorimotor experiences. Both language computation and behavioral rating experiments show that climate robustly affects all dimensions, including not only the sensorimotor ones but also more social-cognitive ones such as *mental-cognition*, *time*, *space*, *number*, *social*, and *emotion* (Figure 3c and 3f). While the detailed mechanisms for these effects remain to be understood, this broad dimensional effect is in line with our intriguing observation of the climate-brain activity associations in the anterior temporal lobe in the human brain. ATLs have long been established to be key regions processing higher-order semantics, binding the distributed semantic dimensional representations and relational structures in language (see reviews in Miyashita, 2019; Lambon-Ralph et al., 2017; Bi, 2021). These findings provide a first direct empirical link between the neurobiology of semantics and the macro-ecological variables. The laterality difference between effects of climate (in the right ATL) and culture (in the left ATL) associated with the corresponding languages warrants further investigation.

Our findings have broad implications for understanding cultural evolution. Previous research has emphasized the broad impacts of ecological variables (e.g., climate) on human sociocultural behaviors (Wormley et al., 2023; Van de Vliert, 2020). Given that information is ultimately processed by the internal models of the human brain for behavior, the variations along the neurobiological semantic structures may serve as a cognitive mechanism underlying such processes. Indeed, our mediation analyses revealed that semantic variations had a significant mediating effect between climate and culture, that is, climate leads to cultural changes partly via semantics. We further identified specific semantic profiles that were associated with different major climate groups (Figure 5b). For instance, the social semantic dimension loads more strongly in languages of tropical regions, which may help explain the previous reports about higher temperatures associating with stronger collectivism (Van de Vliert, 2020). More generally, having identified the robust association between climate and a central cognitive component — semantics, future studies elucidating the detailed neurocognitive mechanistic processes would be critical for understanding the intricate interplay between our living environment and diverse human behaviors, especially in the era of profound climate change.

Limitations

A few caveats and future directions warrant discussion. First, our selection of dimensions in the neurocognitive dimensional structure, while based on existing positive findings regarding cognitive neural semantic organizations, may not be exhaustive or entirely independent. Second, each method has different measures of semantics and different advantages or caveats. The statistical comparisons of the multiple semantic models in Study 1 relied on language text models, which may be sensitive to corpus sizes and text types, and semantic representations derived from text computations tend to underestimate variations stemming from nonlinguistic factors (Günther et al., 2019). The effect size varied across studies, with the variance being explained by environmental variables being higher on the language level (in the language model study) and much smaller in the human individual level behavior and brain activity studies, which might be attributable to many other variables contributing to different measurements. The convergence across these different measures highlights the robustness of the positive findings we discussed. Finally, while our language samples included in the environment-semantic association analyses cover a substantial portion (approximately 1/2–1/3) of the world's major populations across three Studies, they have all gone through varying degrees of modernization. This may lead to an underestimation of the effects of cultural and linguistic factors on semantic structures, which warrants further investigations.

Conclusion

In conclusion, we showed that the semantic representations along the neurobiologically motivated dimensions show greater alignments across diverse languages than control models, with variations along such a structure most strongly predicted by the climate in the region of the corresponding language. These findings highlight the interplay between the biological and cultural evolution mechanisms that underlie semantic meanings across the globe.

Methods

Study 1: Language model study using word embedding data in 53 languages

Language samples and concept list: We investigated 1,016 concepts across 53 languages from 10 distinct language families. The concept list and languages were sourced from the NorthEuralex (NEL) dataset (Dellert et al., 2020). The NEL dataset provided translational equivalent word forms for these concepts, which have enduring and relatively consistent word representations in history and cover important semantic fields (Thompson et al., 2020). Language sample selection proceeded in two steps: First, we identified 61 languages with translated word forms available in the multi-lingual pretrained word embedding models. Second, we excluded 9 languages missing over 25% vector representations for NEL concepts to ensure adequate shared concept coverage between language pairs. Analyses on all 61 languages yielded same results. Detailed language information can be found in Table S2, and the distribution of concept numbers for each language is illustrated in Figure S8.

Multi-language pretrained word embedding model: We obtained semantic representations of concepts using 300-dimensional word vectors from pretrained embedding models available through fastText (https://fasttext.cc/docs/en/crawl-vectors.html). These models were trained on vast corpora from Wikipedia and Common Crawl, with the training data containing billions to hundreds of millions of word tokens for each language, resulting in improved performance for low-resource languages compared to "Wikipedia only" models (see model details in Grave et al., 2018). To validate our results against different corpora types, we also ran replication analyses using additional pretrained models based on Wikipedia and Open Subtitles corpora (Van Paridon & Thompson, 2021), which incorporate speech transcriptions from television shows and movies (Supplementary Text S2).

Construction of different semantic representation models: To compare semantic representations across languages, we employed a semantic projection framework (Grand et al., 2022; Lewis et al., 2019). This approach involves projecting the original 300-dimensional embedding vector representations of 1,016 NEL concepts onto various "anchor" vectors to construct different semantic models (i.e., computing cosine similarities between NEL concept vectors and different anchor vectors).

We excluded words appearing in both target concepts and anchor dimensions to avoid overestimating commonalities. We constructed the following types of models:

Distributional semantic models (local and global). Following Thompson et al. (2020), we projected concepts onto their relationships with other words. We considered two types of measures: distributed local models, using varying numbers of semantic neighbors as anchors and distributed global models, using all the other 1,015 concepts as anchors. We computed cosine similarities between each NEL concept vector and these anchors to obtain distributional semantic representations. For local models, results using the top 100 closest neighbors are reported in the main text.

Semantic feature model. We projected concepts onto human-generated descriptive "feature" words from the Semantic Feature Production Norm (Buchanan et al., 2019). This norm includes approximately 4,000 features words used to describe 4,436 concepts, representing various types of semantic knowledge (e.g., 'is red', 'is mammal', 'lay eggs', and 'live in the water'). As the norms were primarily generated by native English speakers, we translated key feature words in other languages in our samples using Google Cloud Translation API (https://cloud.google.com/translate), excluding Bashkir, Breton, and Sakha due to resource limitations. The semantic feature representation was obtained by computing cosine similarity between each NEL concept vector and the feature word vectors. We conducted analyses using varying numbers of the most frequently nominated feature words (top 100, 200, 500, and 1,000) as anchors, with results from the top 100 feature words reported in the main text.

Neurocognitive semantic model. The neurocognitive semantic model consisted of 13 primary structural dimensions gleaned from neurocognitive semantic research (see Introduction and Table S1 for a list of example empirical references). These dimensions include seven sensory-motor domains (color, shape, taste, smell, sound, touch, and bodily motor) and six core cognitive domains (time, space, number, mental-cognition, emotion, and social). The anchor words for each dimension were selected from the NEL concept list by three native Chinese speakers, who first manually selected words defining or corresponding to each dimension and then reached consensus on a final anchor word list. A total of 122 anchor words were used (see Table S3), with approximately 2-14 anchor words for each dimension. We computed the averaged cosine similarity between each NEL concept vector and the vectors of anchor words for each dimension to obtain a 13-dimensional vector as the neurocognitive semantic representation. Using the original anchor concepts from Binder et al. (2016), which were selected by English speakers, yielded the same results patterns.

Statistical control models. To assess the explanatory power of the above candidate theoretical models for cross-language semantics commonalities, we constructed two statistical control models: a) Random word model. We randomly selected 13 words from the original 1,016 NEL concepts as anchor words and calculated their cosine similarity with the target concepts. b) Random dimension model. We randomly selected 100 anchor words, grouped them into 13 dimensions (corresponding to the number of dimensions of the neurocognitive model) using K-means clustering, and calculated their cosine similarity with the target concepts. Each random model was repeated 10,000 times to obtain the cross-language commonality distributions. We then established the statistical confidence of each theoretical model by comparing the model's cross-language commonality scores within the distribution from the statistical control models.

Estimation of cross-language commonalities: To assess the degree of cross-language commonality across different semantic models, we employed two complementary measures of convergence. Note that these measures differ also in the number of concepts analyzed and their treatment of between-concept variations.

Inter-language correlation analysis. For each semantic representation model, we calculated the Pearson correlation coefficient (r) between the semantic representations of each language pair for all 1,016 concepts. The resulting inter-language correlation (ILC) was then Fisher-Z transformed and averaged across concepts. To compare the ILCs between different types of theoretical semantic representations, we employed the Wilcoxon signed-rank test (two-sided) for paired samples.

Principal component analysis. To further estimate shared variances across all languages, we conducted principal component analysis (PCA) for 204 concepts shared across all 53 languages. For each semantic representation model, we represented each language as a matrix of semantic relations (e.g., for the neurocognitive model, the matrix dimensions were 204×13). We then treated languages as features and semantic relations (reshaped from a matrix into a vector) as samples, and performed PCA across languages. The proportion of variance explained by the first principal component (PC1) was used as an estimate of shared variance for cross-language semantic alignments.

Prediction of colexification network topologies: To investigate whether the neurocognitive semantic models could predict word relations in more diverse language samples, we employed the Database of Cross-Linguistic Colexifications (CLICS version 3.0), a comprehensive cross-language resource containing colexification patterns of approximately 3,000 concepts across 2,681 languages in 180 language families (Rzymski et al., 2020), capturing instances where two or more concepts are expressed by the same wordform within a language. The hypothesis here is that if the neurocognitive semantic model outperforms statistical control models (random word models and random dimension models) in predicting word topological patterns in the colexification network, it would indicate the generalizability of these structures to a broader range of languages.

We conducted separate analyses using colexification networks derived from: a) The entire CLICS language sample (N = 2,681); b) A subset of non-Eurasian languages from the CLICS database. For 165 of the 204 concepts used in the pretrained embedding analyses, we extracted the following network properties from the CLICS database: edge weight, weighted common neighbors, community structures based on Louvain and Infomap algorithms. These measures capture first-order, second-order, and global information in the network, respectively, and are widely used to quantify semantic similarity across languages (Tjuka et al., 2024; Jackson et al., 2019; Fu et al., 2023). We computed an overall pairwise similarity score as the average of these four metrics and then correlated these network similarities with the neurocognitive semantic relations from the 53 languages in our embedding data using Spearman correlation. The correlations were averaged across the 53 languages to obtain a mean correlation for each network (full sample and non-Eurasian subset). The statistical confidence of the neurocognitive models' predictability for colexification network properties is established by comparing the model's Spearman correlation coefficients with the distribution of correlation coefficients from the statistical control models (N = 1,000 times).

Prediction of inter-language semantic variations: To understand what environmental factors may account for the variations in the universal semantic structure, we carried out representational similarity analysis (RSA) between inter-language semantic variation and the distances of the four salient ecological variables, including the geography, climate, linguistic history, and culture. Specifically, we tested the association between the lower triangle of the semantic representational dissimilarity matrix (RDM) across languages and the lower triangle of RDMs for each or composite of these environmental variables (excluding the main diagonal elements).

Environmental variables. We obtained pairwise distances on these four environmental variables based on the languages' coordinates provided by Glottolog 4.6 (Hammarström et al., 2022). The geographic distances were calculated as the geodesic distances between the locations of languages on the Earth's surface. The climate distances were calculated as the scaled Euclidean distance based on the estimates of 19 bioclimate variables from WorldClim (Fick & Hijmans, 2017; see Table S10 for the full list). The 19 bioclimate variables were derived from the monthly temperature and precipitation, which are often used in species distribution and related ecological modeling. The distances of linguistic history were estimated based on cognates of the NorthEuralex wordlist, using LingPy (List & Forkel, 2023) with the LexStat method (List, 2014). The cultural distances were retrieved from Thompson et al. (2020), which was calculated based on the eco-cultural traits in the D-place dataset (Kirby et al., 2016), including societies' housing, labor institutions, marriages, and political systems.

Representational similarity analysis. The inter-language RDMs were first constructed for semantic variations and for each environmental variable. The semantic RDM was constructed by computing the distance (i.e., 1 – Pearson correlation, with Fisher-Z transformed) of averaged concepts' neurocognitive semantic vectors between language samples. After obtaining these inter-language RDMs, we performed nonparametric Spearman correlations for their raw associations and built multiple regression models (with language pairs in the lower triangle of RDMs rank-transformed) to estimate how the semantic variations across languages could be explained by the environmental variables. The linear mixed regression model was further conducted to estimate the fixed effects of each environmental variable with a crossed random-effects structure that nested language pairs within language families considered, to account for potential non-independent language sampling (Chen et al., 2017; Thompson et al., 2020; see Supplementary Text S3 for details and other ways to control non-independence). Effects of environmental factors on cross-language semantic variations at the single dimension level were also assessed through linear mixed regression models. Mediation analyses were conducted to explore the mechanisms linking climate, semantic variations, and cultural factors. Direct and indirect effects were assessed, with 95% confidence intervals established through nonparametric bootstrapping (N = 5,000).

Study 2: Human participants' behavioral ratings in 8 languages

Participants: We recruited a diverse sample of 272 online participants from 58 city sites across 8 countries, representing distinct languages: Arabic (Egypt), Chinese (China), English (USA), Hindi (India), Japanese (Japan), Korean (South Korea), Russian (Russia), and Spanish (Spain). Participants were recruited through the Appen crowdsourcing platform (http://www.appen.com). All participants were confirmed to be native speakers residing in their respective targeted sites. To ensure geographical diversity while minimizing intercorrelations among environmental variables of interest, we strategically selected 6-8 geographically dispersed sites within each country (Figure S6; Table S6). To ensure data quality, we implemented a stringent inclusion criterion. Participants whose rating vector correlated less than 0.5 with the averaged group vector within their respective language were excluded from the main analyses. This resulted in the exclusion of 19 participants. The final sample size was 253 participants, with a balanced distribution of 30 to 34 participants per country. This study was approved by the Institutional Review Board State of the Key Laboratory of Cognitive Neuroscience and Learning, Beijing Normal University.

Concept list: For this study, we used the Swadesh 207-Word list, which has been extensively studied in historical and comparative linguistics and is considered to represent the core basic vocabulary of human languages (Swadesh, 1952). The 207 words also sufficiently overlapped with the NEL concept list used in Study 1. To obtain translated word forms of these concepts across our target languages, we sourced initial word forms from the PanLex Swadesh database (Kamholz et al., 2014) and asked professional translators to review them. In cases where PanLex provided multiple word forms for a single concept, our translators were instructed to select the most commonly used ones. To mitigate potential ambiguity, particularly for polysemous words, we accompanied with contextual specifications (e.g., lie (as in a bed)). The final wordforms were provided in Table S7.

Rating instructions: To evaluate the 13-dimensional neurocognitive semantic structures, participants were instructed to rate concepts on the extent of association with specific dimensions. Our approach was adapted from Binder et al. (2016), providing some forms of association for each dimension (e.g., for color, the association could be “This word refers to something that has a characteristic color (e.g., eggplant)”, “This word describes the change in color (e.g., fade)”, or “this word directly refers to a particular color (e.g., red)”). To support the participants’ understanding, we included example words with high and low loadings from Binder et al.’s questionnaire. To mitigate potential cross-cultural biases, we excluded example words with below-average frequency based on word frequency data in Binder et al. (2016) and example words that could introduce cultural biases. The English rating instructions were translated into 7 other languages using multi-proofreading processes (Supplementary Text S5). The rating instructions for each language can be found in the link (https://osf.io/suyeb/?view_only=c0ca6847b89d4257807ee342463ac6b8).

Online rating procedures: Participants completed a prescreening process followed by three sessions of the conceptual rating task.

Prescreening. To ensure native speaker selection, we employed a rigorous prescreening process comprising self-reports and a 5-minute audio transcription test in the target language. We collected detailed language background and demographic information, including age, gender, education level, ethnicity, subjective socioeconomic status (SES; Adler et al., 2000), second language proficiency, country of upbringing before age of 7, and current region of residence. Participants who were nonnative speakers, failed the transcription test, had lived in a foreign country before the age of 7, or were currently residing in foreign countries were not invited to the rating task. Moreover, those who self-reported high proficiency in a second language (5 on a 5-point Likert scale, indicating “upper intermediate and above”) were also excluded. For Indian participants, criteria were adjusted due to the country's multilingual nature, excluding only those with high proficiency in languages of interest (e.g., English).

Rating Task. Eligible participants completed a rating task comprising three 50-minute sessions. Each session involved rating approximately 70 words on 13 neurocognitive dimensions. The 207 concepts were pseudorandomly shuffled into 30 wordlists, which were then randomly assigned across the three sessions. To ensure quality control during the processes, three catch trials using high-loading examples from the instructions were randomly inserted into each wordlist. The task automatically terminated if erroneous (low) ratings were detected on control questions. Pearson correlations were computed between each participant's rating vector and the averaged group vector within each language. Participants with correlations below 0.5 were excluded from further analysis. The final sample consisted of 253 participants. Analyses including all participants yielded similar results.

Prediction of cross-language speakers' semantic variations: An inter-subject correlation matrix was constructed by calculating Pearson correlation coefficients between each subject pair's ratings on 207 concepts across 13 dimensions (2,691 ratings per subject). To investigate the explanatory power of macro environmental variables in understanding cross-language (neurocognitive) semantic variations at the speaker level, we employed RSA between inter-subject semantic variations and the distance of the four salient ecological variables, including the geography, climate, linguistic history, and culture.

Environmental variables. We obtained pairwise distance on these four variables based on participants reported geographic residing areas (city/county). The site-level geographic coordinates were obtained using the Bing Maps API (https://www.bingmapsportal.com/). The geographic distances were calculated as the geodesic distances between individuals' site locations. The climate distances were calculated as the scaled Euclidean distance based on the 19 bioclimate variables from WorldClim (Fick & Hijmans, 2017). The linguistic history and cultural distances were taken from the language/country level distance measurements from Study 1. Additionally, we constructed a measure of demographic distances based on scaled Euclidean distances of participants' demographic variables, including age, gender, education level, and SES.

Representational similarity analysis. The inter-subject RDMs were first constructed for semantic variations and for each environmental variable. The semantic RDM was constructed by computing the distance (i.e., 1 – Pearson correlation, with Fisher-Z transformed) of concatenated concept' neurocognitive semantic vectors between individuals. After obtaining these inter-subject RDMs, we performed nonparametric Spearman correlations for their raw associations and built multiple regression models (with subject pairs in the lower triangle of RDMs rank-transformed) to estimate how the semantic variations across languages could be explained by the environmental variables. The linear mixed regression model was further conducted to estimate the fixed effects of each environmental variable with a crossed random-effects structure that nested subject pairs within language families considered to account for potential non-independent sampling (Chen et al., 2017; see Supplementary Test S3 for details and other ways to control non-independence; Thompson et al., 2020). Effects of environmental factors on cross-language semantic variations at single dimension level were also assessed. Mediation analyses were further conducted to explore the mechanisms linking climate, semantic variations, and cultural factors. Direct and indirect effects were assessed, with 95% confidence intervals established through nonparametric bootstrapping (N = 5,000).

Study 3: Human participants' brain activity patterns in 45 languages

fMRI dataset: This study utilized an open-access multi-language fMRI dataset (Malik-Moraleda et al., 2022) available at the OSF repository (https://osf.io/cw89s). The dataset comprises neural activity measurements during a language comprehension task performed by 86 native speakers across 45 languages from 12 language families. Eighty-six participants (43 males; age range: 19-45 years) were recruited from Boston, the United States. All participants were proficient in English in addition to their native language. Participants underwent a passive listening task during fMRI scanning. They were presented with auditory stimuli consisting of passages from “Alice in Wonderland” translated into their native languages. The stimuli were presented in two conditions: intact native-language condition and acoustically degraded-language condition (control condition). This contrast between the two conditions is commonly used to obtain neural activities that are related to high-level language processing, including semantics. We obtained the preprocessed whole-brain contrast maps (t-value maps comparing intact native-language and acoustically degraded-language conditions) for all 86 participants from the OSF repository for our analysis. Detailed information on subject characteristics, imaging acquisition procedures, task designs, data preprocessing and first-level modeling are referred to Malik-Moraleda et al. (2022).

Regions of Interest: We focused our analysis on neural activities in 12 regions (6 left hemisphere, 6 right hemisphere) within the language network (Fedorenko et al., 2010). To identify regions encodes cross-language alignment in the neurocognitive 13-dimensional semantic space, we calculated inter-subject neural RDMs based on individual t-value maps for each of the 12 language-responsive regions. The neural RDMs were then correlated with the semantic RDMs of participants' native languages (computed in Study 1) using Spearman's rank correlations on the language samples shared between Study 1 and Study 3. Regions demonstrating statistically significant correlations (i.e., correlated with cross-language semantic alignments) were considered as our primary regions of interest (ROIs) for further analysis.

Prediction of cross-language speakers’ neural variations: We investigated whether the climate and cultural effects were reflected in cross-language speakers' neural activity patterns using RSA methods. Inter-subject correlation matrices were constructed from individual t-value maps for the previously identified ROIs.

Environmental variables. We obtained pairwise distances on environmental variables by taking the coordinates of participants' native languages, based on Glottolog 4.6 (Hammarström et al., 2022). For these coordinates, the climate distances were calculated as the scaled Euclidean distance based on the 19 bioclimate variables from WorldClim (Fick & Hijmans, 2017). The cultural distance measures were taken from Study 1. The geographic distances were calculated as the geodesic distances. The language family distances were incorporated as a binary measure (0 for the same family, 1 for different families), circumventing the need for cognate calculations on specific wordlists.

Representational similarity analysis. To test if the environmental variables systematically affect neural activity patterns, we examined the relationship between the RDMs and the environmental RDMs across individuals. We constructed two linear mixed models that incorporated random intercepts for each participant dyad to account for data non-independence, following recent practices in inter-subject neural data analysis (Chen et al., 2017): a) Base Model: Incorporating geographic distance and linguistic family as phylogenetic controls; b) Full Model: Additionally including climate and cultural distances. A superior fit of the extended model compared to the base model would indicate significant effects of climate and cultural distances in explaining neural RDMs. Beta estimations were reported to quantify the unique effects of climate and culture.

Acknowledgments:

We thank Haojie Wen, Xi Yu, Dingchen Zhang, Shuang Tian, and Shuyue Wang for help and comments on earlier drafts of the manuscript.

Author Contributions: YB conceived and supervised the research; ZF performed the research; YC, TZ, and YL collected rating data; ZF and YC analyzed the data; XW contributed valuable discussions; and YB, ZF, and XW wrote the paper.

Competing Interests: The authors declare no competing interests.

Funding: This work was supported by the STI2030-Major Project (2021ZD0204104 awarded to YB), the National Natural Science Foundation of China (31925020, 82021004 awarded to YB, 32171052 to XW), and the Fundamental Research Funds for the Central Universities (to YB).

Data and materials availability: Data and codes used in this study were deposited to OSF https://osf.io/suyeb/?view_only=c0ca6847b89d4257807ee342463ac6b8 .

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Figures

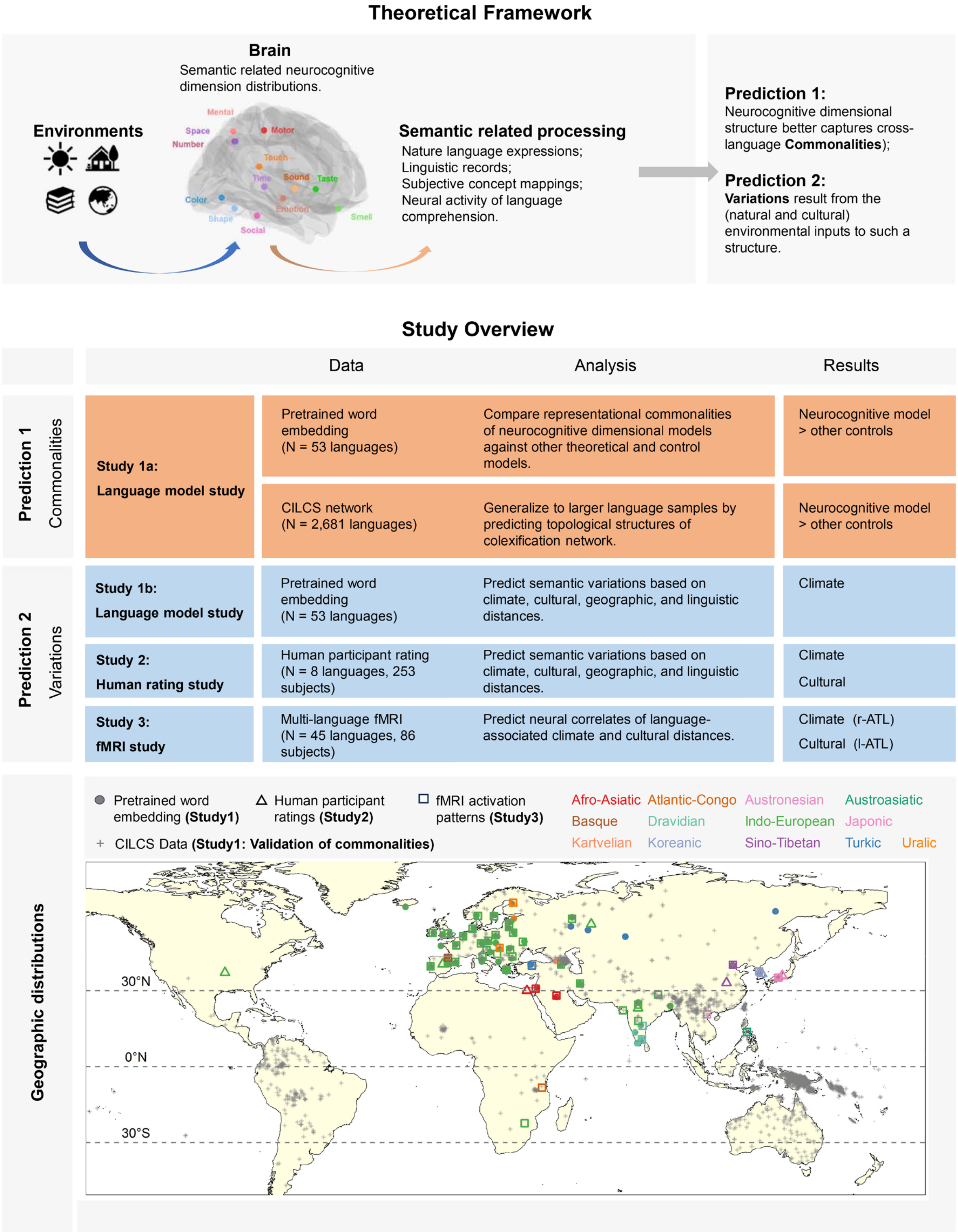

Figure 1. Theoretical framework and study overview. The core research question investigates the principles organizing cross-language semantic space by examining commonalities and variations observed in various types of data: natural language expressions, linguistic records, subjective concept mappings, and neural activities related to language comprehension. The theoretical framework

suggests that the neurocognitive dimensional structure, as a shared biological constraint, better captures cross-language commonalities, while variations result from natural and cultural environmental inputs to such structure. The analysis involves three main studies: 1) Language model study; 2) Human rating study; and 3) fMRI study. The brain illustration (upper left) visualizes probabilistic peak activations associated with various high-level sensory-motor and cognitive domains, generated using NeuroQuery, a meta-analysis tool for mapping neural terms (Dockès et al., 2020). The world map (bottom) shows the geographic distribution of language samples across the three studies. For Studies 1 and 3, we used language geographic coordinates from Glottolog 4.6 (Hammarström et al., 2022). For Study 2, we used averaged location coordinates reported by participants for each language sample.

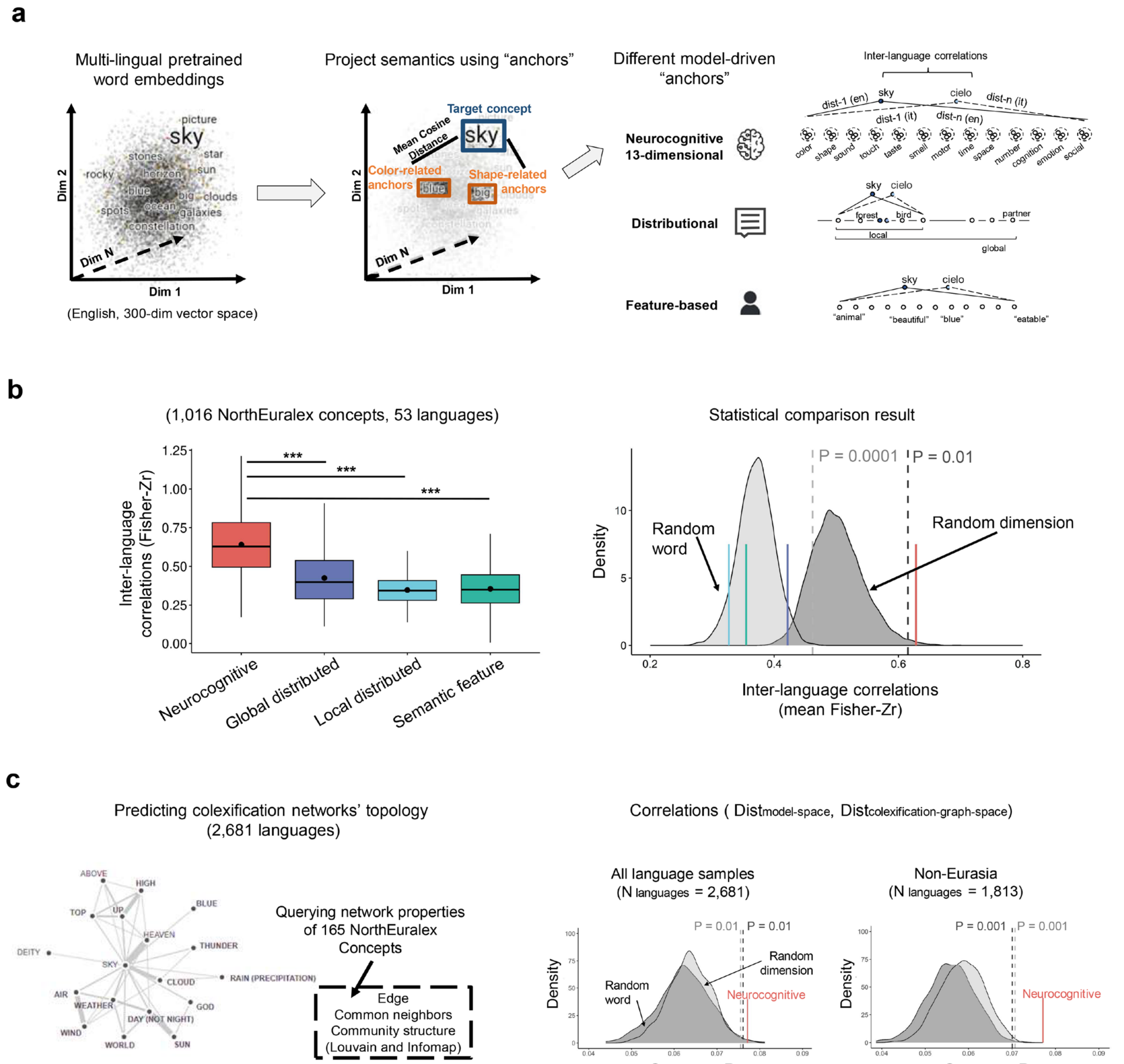

Figure 2. Commonality of the neurocognitive semantic structure across languages using language computational analysis (Study 1a). a. Semantic construction methods in the pretrained word embedding data analyses. Pretrained 300-dimensional word embedding data of 53 languages from 10 language families were included. Embedding vectors of target concepts were projected onto three theoretical semantic representations and compared for cross-language commonalities: neurocognitive, distributional (local and global), and feature-based models, each with different anchor words/dimensions (see Methods). **b**. Semantic commonality results. Left panel: Boxplots show the distribution of the inter-language correlations across language pairs for the four semantic models, with the neurocognitive structure showing higher alignment than distributional or feature-based models. Right panel: Comparisons of mean inter-language correlations between the four semantic models and two random control models: random word models (randomly selecting 13 NEL words as anchor words 10,000 times; light gray area) and random dimension models (randomly selecting 100 NEL words and grouping them into 13 dimensions 10,000 times; dark gray area). The mean inter-language correlation of the neurocognitive model (the red line) was significantly higher

than that of the two control models (*P*s < 0.01); those of the other models were not. **c.** Generalization of 13-dimensional neurocognitive space to larger language samples using the colexification network data. Left panel: Visualization of the CLICS data and network properties representing semantic distance in the colexification topology space. Right panel: Density plots comparing association patterns between semantic distances in the original 53-language embedding-derived neurocognitive space and the colexification topological graph space. The analysis includes all language samples (N = 2,681) and non-Eurasian languages (N = 1,813; encompassing South America, North America, Africa, Papunesia, and Australia, excluding unclassified languages). The neurocognitive model's performance (*P*s < 0.01, red line) is at the upper bound of the random model distributions, demonstrating robust cross-linguistic generalizability.

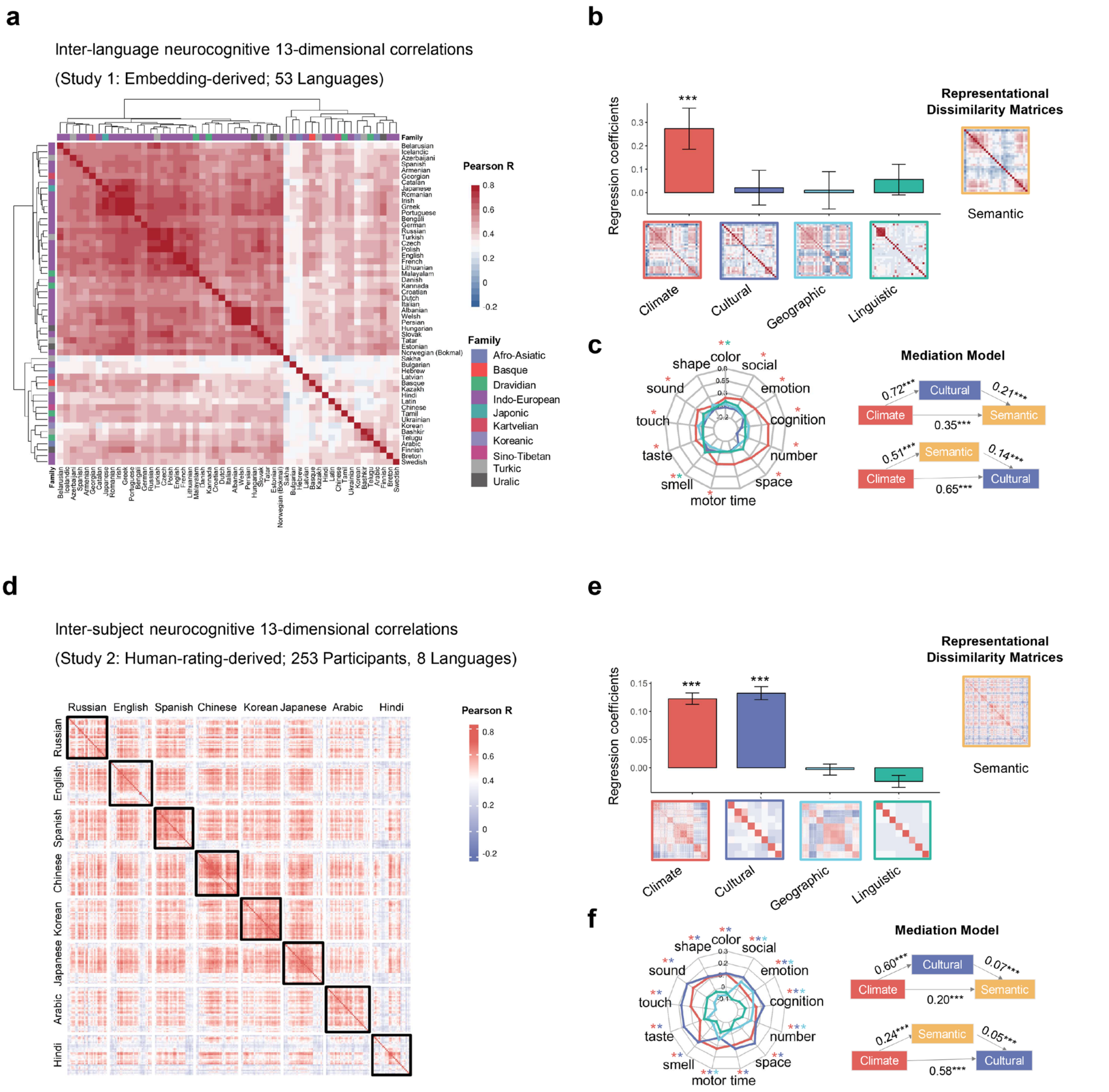

Figure 3. Environmental predictors of neurocognitive semantic variations in word embedding data (53 languages; Study 1b) and human rating data (253 participants, 8 languages; Study 2). a. Inter-language correlation matrix of 53 languages based on the 13 neurocognitive dimensional structure. The dendrogram shows the hierarchical clustering of languages by correlation distances, with languages color-coded according to language family. **b.** Linear mixed regression models predicting cross-language semantic variations with environmental RDMs (climate, linguistic history, geography, and culture). Standardized regression coefficients for each factor are shown, with the factor RDM displayed below each bar. **c.** Left panel: Dimension-specific environmental effects. Radar plot displaying standardized beta coefficients from regression models for each of the 13 neurocognitive dimensions across environmental variables. Right panel: Mediation analyses testing the relationships among climate, semantic, and cultural variations. **d.** Inter-subject correlation matrix of the neurocognitive semantic representations, each cell representing the Pearson correlation coefficient

of the ratings on the 207 concepts and 13 dimensions (2,691 ratings) for each pair of 253 subjects. Cells in the black box are the intra-language correlations. **e.** Linear mixed regression models predicting the inter-subject semantic correlation distance using four environmental RDMs (climate, linguistic history, geography, and culture) with a demographic RDM (the Euclidean distance of participants' age, gender, education level, and SES) as the control variable. Standardized regression coefficients for each factor are shown, with the factor RDM displayed below each bar. **f**. Left panel: Dimension-specific environmental effects. Radar plot displaying standardized beta coefficients from regression models for each of the 13 neurocognitive dimensions across environmental variables. Right panel: Mediation analyses testing the relationships among climate, semantic, and cultural variations. Error bars represent 95% CIs. Significance levels: ***, $P < 0.001$; **, $P < 0.01$; *, $P < 0.05$.

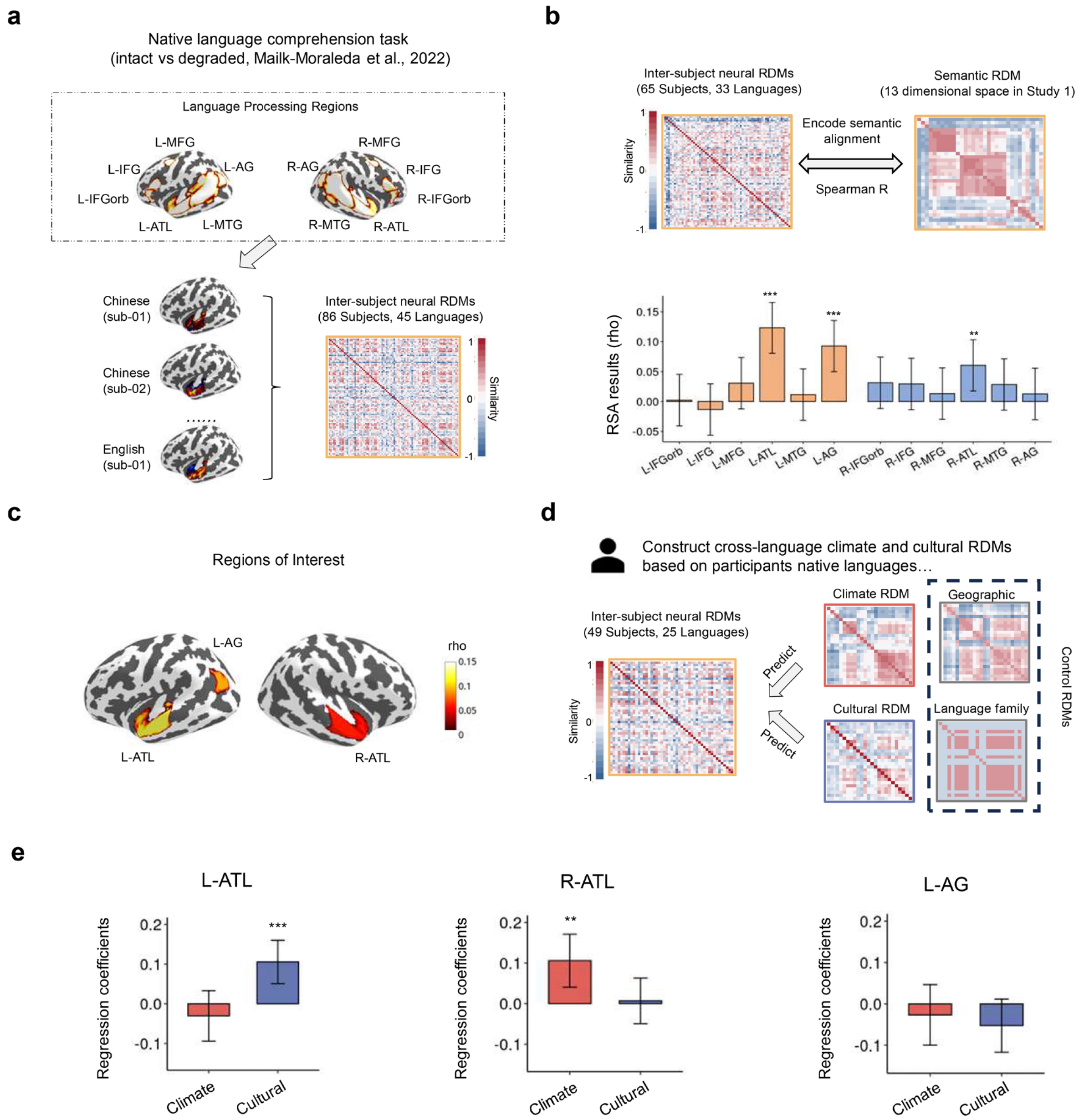

Figure 4. Neural correlates of environmental effects on language processing (Study 3). a. Methodology for constructing neural RDMs from 86 subjects across 45 languages within the high-level language processing network (Fedorenko et al., 2010). Inter-subject neural RDMs were derived from the contrast between intact and degraded native language processing (Malik-Moraleda et al., 2022). **b**. Correlation between neural variations across speakers (measured by inter-subject neural RDMs) and embedding-derived semantic variations associated with their native languages (obtained from Study 1). The bar plot depicts correlation results across all 12 brain regions. **c**. Brain map highlighting significant correlations (*P*s < 0.05) in bilateral ATLs and the left AG, indicating that these regions encode cross-language semantic alignments in 13-dimensional space (derived in Study 1). **d**. Methodology for constructing environmental RDMs and modeling. Environmental factor RDMs were obtained for participants' native languages. **e**. Climate and cultural effects on neural activity patterns. Beta estimation plots illustrating climate and cultural factor effects on neural pattern similarities in

each ROI. Significant climate effects were found in the right ATL, while cultural factors significantly influenced the left ATL. Abbreviations: ATL, anterior temporal lobe; IFG, inferior frontal gyrus; IFGorb, inferior orbital frontal gyrus; MFG, middle frontal gyrus; MTG, middle temporal gyrus; AG, angular gyrus. Significance levels: *** $P < 0.001$; ** $P < 0.01$; * $P < 0.05$.

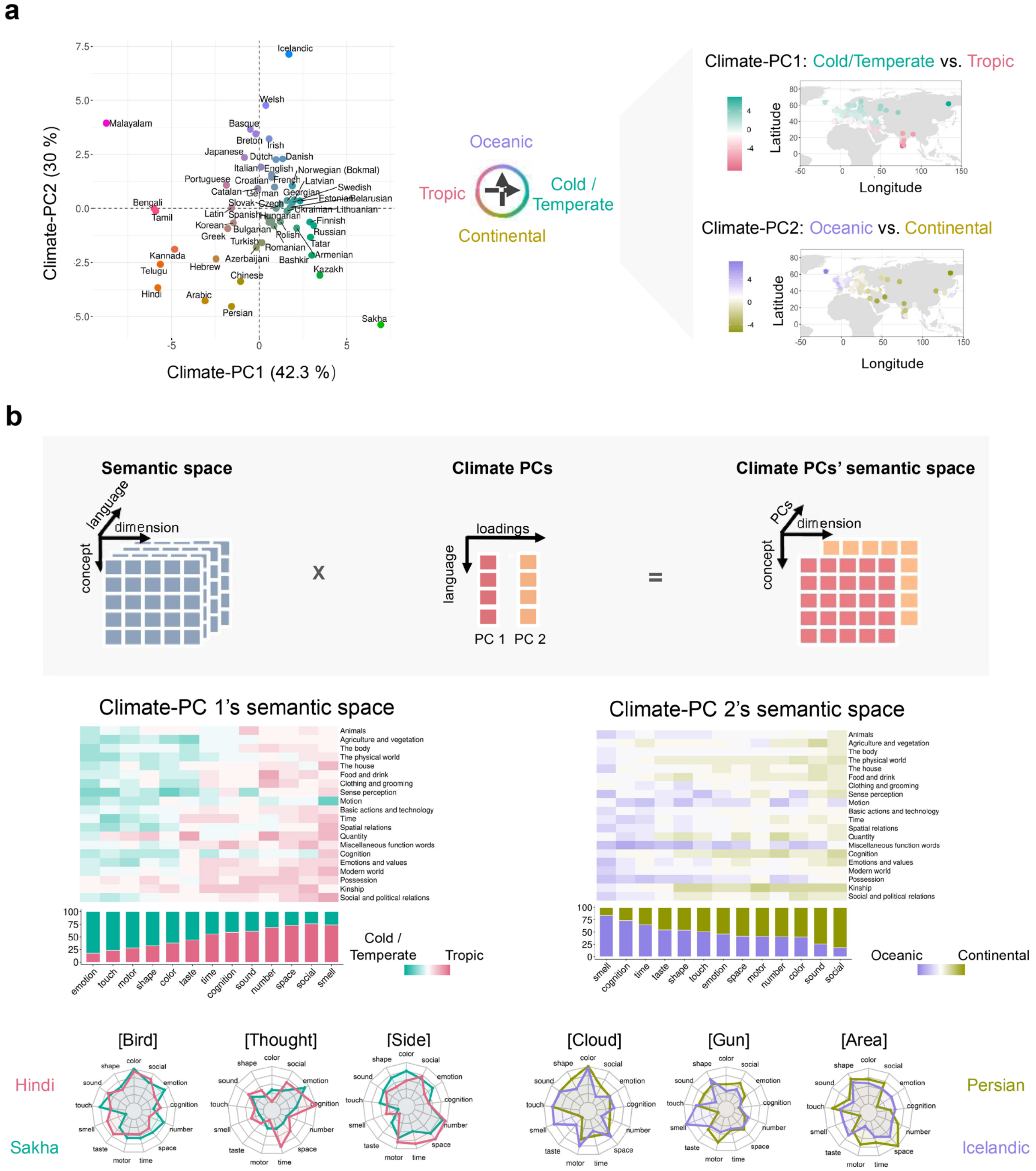

Figure 5. Semantic variation structures associated with different climate groups. **a.** Climate typology and distribution of 53 languages. PCA on the 19 climate variables of the geographic coordinates of 53 languages revealed that the first two principal components captured 72.3% of climate variations, and they were termed "tropical vs. cold/temperature" climates and "oceanic vs. continental" climates, respectively, according to the loadings of climate variables on each PC. The right panel shows the geographic mapping of climate PCs. **b.** Semantic profiles associated with each climate PC. The top panel illustrates how we projected the semantic spaces of 53 languages (obtained in Study 1) onto

the Climate PC1 and PC2 axes. The middle panel shows the domain-level semantic profiles associated with each Climate PC (see Figure S7 for the concept-level profile). Higher values along a particular direction of PCs indicate that the given climate type tends to have stronger semantic relations. The bar plots below show the semantic association ratio of the two directions along each PC, calculated as the summed values in one direction divided by the total summed values in both directions. The bottom panel shows examples of loading patterns of specific concepts on 13 neurocognitive semantic dimensions obtained from the language data.