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 communications. 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 neurocognitive theories, with the consensus framework that semantics are derived from sensory experiences, with a set of dimensions being identified as biologically salient in neuroscientific studies. We operationalized word semantic representations with this set of specific dimensions, using computational models (53 languages' word embedding data; Study 1), human behavioral 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 the 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 (Kay & Kempton, 1984; Majid et al., 2004; Wierzbicka, 1992b). 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 have identified common concepts across semantic domains such as color (Berlin & Kay, 1991) and emotion (Ekman, 1992; Wierzbicka, 1992a), while also revealing different words for the same perceptual referents, culturally bound words resistant to translation, and different categorization systems (Majid et al., 2004; Majid et al., 2015; Majid et al., 2018; Passmore & Jordan, 2020). Recent advances in computational linguistics allow for cross-linguistic comparisons through analysis of word representations derived from extensive language corpora (see review, Jackson et al., 2022). These approaches assess cross-linguistic semantic alignment (e.g., *beautiful* in English and *bella* in Italian) by comparing their distances to a set of "*anchor words"* in their respective high-dimensional representational spaces, allowing for meaningful comparisons across languages. The selection of different anchor word sets (whether domain-specific, proximally neighboring, or the entire word space) and the utilization of diverse data types (including word embeddings and colexification networks) have yielded different results and conclusions accordingly, supporting either word semantics being "innate" (Youn et al., 2016) or culturally driven (Lewis et al., 2023; Thompson et al., 2020). It is difficult to evaluate whether these differences reflect those 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 the intrinsic way in which the human brain represents semantic knowledge offers a strong candidate framework for understanding both cross-linguistic semantic universality and variation. 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 such a biological structure would respond to different environmental inputs (e.g., naturally and culturally varied), resulting in phenomenal

variations. Neurocognitive research reveals a consensus framework that semantic representation in the brain is derived from sensory (and language) experiences in ways that respect 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 (Fernandino et al., 2016; Fernandino et al., 2022; He et al., 2013; Martin et al., 1995). Lesions in the brain lead to deficits along the lines of these sensory-motor modalities and domains (Buxbaum et al., 2000; Capitani et al., 2003; Miceli et al., 2001). 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 (Bi, 2021; Bottini et al., 2020; Mahon & Caramazza, 2011; Wang et al., 2020). Several mainstream neuroanatomical semantic models — including GRAPES (Martin, 2016), Embodied Abstraction (Binder & Desai, 2011), Hub-and-Spoke Model (Lambon-Ralph et al., 2017; Patterson et al., 2007), and Neural Dual Coding Theory (Bi, 2021) — converge in their recognition of this foundational biological structure underlying semantic representation, 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 representations 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.? This neurocognitive approach also offers methodological advantages for cross-linguistic comparison. By focusing on dimensions with established neural correlates, we create a controlled space where both universal patterns and meaningful variations can be understood against a consistent "backbone" of biological universality. Such dimensional structures not only reveal fundamental commonalities in semantic organization across languages due to our shared neural architecture, but also filter out potentially idiosyncratic semantic dimensions to highlight variations specifically along sensorimotor and core-cognitive channels.

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 distribution-based models (Figure 2a) that do not directly incorporate the neural architecture, 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.

Second, regarding variations along this dimensional structure, the intrinsic assumption of the

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

142
143 **Study overview**
144   We conducted a series of studies to test the above predictions about cross-language alignment
145 patterns through multiple approaches – computational, behavioral, and neural measures – for
146 convergence (Figure 1). Study 1 involved language computational analyses on large-scale multilingual
147 pretrained word-embedding data (Grave et al., 2018). For the universality prediction, we compared
148 the extent of commonalities captured by the target model (with the 13 neurocognitive dimensions as
149 *anchor words*) and alternative models (different types of *anchor words*). For the variation prediction,
150 we examined the relationship between variations along this neurocognitive dimensional structure
151 and ecological variables across languages. Such models have the advantage of analyzing large-scale
152 language patterns, but the relationship of ecological variables with the human mind/brain is
153 approached indirectly through computational relationships. Thus, in Study 2, we collected human
154 individual semantic behavioral ratings on these 13 dimensions, and in Study 3, we analyzed brain
155 activity patterns during language comprehension, linking cognition and biology variations more
156 directly with the ecological variables of interest. Figure 1 (bottom panel) illustrates the geographic
157 distribution of language samples across three studies, with detailed language information provided
158 in Table S2.

159
160
161 **Results**

162
163 **Commonalities on the neurocognitive semantic structure**

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

166
167   We focused on the NorthEuralex (NEL) wordlist, which provides 1,016 concepts across 107
168 languages. Among them, 53 languages (spanning 10 language families) were well covered in the
169 recently developed word embedding databases (fastText multilingual word vectors; Grave et al.,

170   2018). These databases provided 300-(hidden)-dimensional word embedding vectors for a large
171   number of languages, pretrained on vast corpora comprising billions of words for each language. For
172   each target concept in each language, we projected its embedding onto different sets of anchor words
173   based on different models (see below), i.e., computing the target-anchor cosine distances (see an
174   illustration of construction processes in Figure 2a; see also the anchor word approach in Chersoni et
175   al., 2021; Grand et al., 2022; Lewis et al., 2019). Distances to different model-driven anchor sets were
176   taken as the model-based semantic representations for the target concepts, based on which cross-
177   language comparisons were performed.

178   <u>Constructing different model-anchor-based semantic representations from word embedding</u>
179   <u>data.</u>

180   We performed cross-linguistic comparisons of semantic representations obtained based on
181   different semantic models. All semantic representations were obtained using an anchor word
182   approach (i.e., essentially all are distributional semantic methods), and the key difference is what
183   types of words were used as anchors for representations. Different anchor words were selected based
184   on different model principles:

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

189   *Semantic feature models*. The psycholinguistic tradition employs semantic feature models based
190   on human-generated decompositional features (e.g., "has fur", "is round"), representing concepts as
191   binary or weighted vectors indicating the presence/absence or strength of each feature (Buchanan et
192   al., 2019; McRae et al., 2005). To adapt this approach for cross-linguistic comparison, we represented
193   the 1,016 concepts using their embedding distance patterns with the 100 most frequent feature
194   words from Buchanan et al. (2019).

195   *Neurocognitive semantic models*. Neurocognitive semantic models, like semantic feature models,
196   assume decompositional representation but highlight a set of underlying "primitive" dimensions
197   constrained by the human brain. We identified 13 primary structural dimensions from neurocognitive
198   semantic research (see Introduction and Table S1 for a list of example empirical references). Anchor
199   words corresponding to these dimensions were manually selected from the NEL concept list (see
200   Methods for details; anchor word list shown in Table S3). Concepts were projected onto these 13
201   neurocognitive salient dimensions by averaging semantic distances of anchor words within each
202   dimension. Our text-derived dimension loadings significantly correlated with the human rating data
203   reported in Binder et al. (2016) (Pearson r = 0.42, $P < 1 \times 10^{-16}$; see Figure S1 for details), consistent
204   with previous findings on subjective-rating validity for the dimension computation (Chersoni et al.,
205   2021).

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

214 models' distributions.

215 Commonalities across languages: Better captured by neurocognitive models

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

219 *Inter-language correlation results.* To quantify cross-language similarity, we computed Fisher's r-
220 to-Z transformed Pearson correlation coefficients between model-based semantic representations
221 for each language pair. As shown in Figure 2b (left panel), the neurocognitive-dimensional semantic
222 representation had greater cross-language similarity compared to the other representation types
223 (mean Fisher-z-transformed r: $M_{neurocognitive} = 0.63$, SD = 0.19; $M_{distributional (global)} = 0.42$, SD = 0.17; $M_{distributional (local)} = 0.33$, SD = 0.10; $M_{semantic feature} = 0.35$, SD = 0.13; neurocognitive vs. distributional
225 (global): Wilcoxon test V = 950123, $P < 1 \times 10^{-16}$; neurocognitive vs. distributional (local): Wilcoxon
226 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
228 (local) and feature models (see Figure S3). Figure 2b (right panel) illustrates that the mean inter-
229 language correlation of neurocognitive models (depicted by red vertical line) exceeded the upper
230 ends of distributions of random word models (depicted by light gray area; P < 0.0001) and random
231 dimension models (depicted by dark gray area; P = 0.005), whereas the other types of theoretical
232 models did not demonstrate this pattern.

233 *Principal component analysis results.* We also employed a complementary PCA on 204 concepts
234 common to all 53 languages, treating languages as "features" and semantic patterns as "samples".
235 This approach assumes that a universal semantic structure would manifest as a relatively high first
236 component (PC1), with the variance explained by PC1 reflecting the degree of universality (Cole et al.,
237 2014; Romney et al., 2000). The neurocognitive-dimensional representation of concepts again
238 showed a greater amount of universality (neurocognitive: 44.31%; global-distributional: 34.16%;
239 local-distributional: 36.38%; feature-based: 34.45%). Similar to the inter-language correlation
240 findings, in comparison with statistical random models, the neurocognitive model, not the other
241 models, was positioned at the upper bounds of their distributions, signifying a relatively universal
242 semantic structure (P < 0.0001 and P = 0.01, respectively). Detailed results, including the scree plot
243 and neurocognitive structure PC1 matrix, are presented in Supplementary Text S1 and Figure S2.

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

246 Generalization to colexification networks with 2,681 languages

247 To test the generalizability of neurocognitive semantic structures beyond these initial 53
248 languages, we investigated whether the neurocognitive semantic model could predict word relational
249 patterns in a larger, more diverse language sample. Given the challenges of obtaining semantic
250 representations for low-resource languages, we utilized the database of Cross-Linguistic
251 Colexifications (CLICS), which contains colexification patterns from 2,681 languages (Rzymski et al.,
252 2020). We employed common topological network metrics, including edge, common neighbors, and
253 two community-based measures (Louvain and Infomap algorithms), and used the average distance
254 across these four metrics as the word distance in the topological graph space. The hypothesis here is
255 that if the neurocognitive semantic model outperforms statistical control models in predicting word
256 topological patterns in the colexification network, it would indicate the generalizability of these
257 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 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 Ps < 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

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 experience, including both natural and cultural environmental factors. The following variables were considered: climate, geographic, linguistic history, and cultural 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 this end, we implemented a consistent analytical framework across all three studies (i.e., studies with word embeddings, behavioral ratings, and neural activity data). At the language level (aggregating participants where applicable), we constructed linear mixed models that included all four variables of interest simultaneously – geographic, cultural, linguistic history, and climate variables – with random intercepts for language families to account for phylogenetic relatedness (Jackson et al., 2023; Thompson et al., 2020). This approach allowed all factors to compete within the same model, revealing their unique contributions to semantic variations. For Studies 2 and 3, we additionally conducted predictions at the individual subject level, confirming that patterns remained

302 consistent across analytical scales.

303

304 <u>Study 1b – Language computational study using word embedding data in 53 languages (variation)</u>

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306 We employed representation similarity analysis (RSA; Kriegeskorte et al., 2008) to quantitatively
307 model cross-language variations in semantic representational geometries by regressing the semantic
308 dissimilarity representational matrix (RDM; Figure 3a) on the RDMs of our selected environmental
309 variables. Data on environmental variables for 53 languages were extracted from various official
310 public databases using latitude and longitude provided by Glottolog 4.6 (Hammarström et al., 2022).
311 The sample sizes (i.e., language pairs) varied depending on the availability of the environmental data.
312 *Association between neurocognitive semantic structural variation and environmental variables.*
313 Correlation analyses first revealed moderate associations between these four environmental RDMs
314 and the semantic RDM (Spearman ρs = 0.39 – 0.53, $Ps < 1 \times 10^{-16}$; Table S4). Within a sample of 29
315 languages (406 language pairs) where all four environmental variables were available, they
316 collectively explained 28% of the semantic (neurocognitive) space variations (Spearman $\rho = 0.52$; P <
317 1×10^{-16}; Figure 3b).
318 We then employed a linear mixed regression model to assess the unique effect of each
319 environmental factor. As indicated in Figure 3c, climate showed the strongest unique explanatory
320 effects ($\beta = 0.28$, 95% CI = [0.20, 0.37], P = 1.50×10^{-9}). Linguistic history also showed significant effects
321 (β=0.22, 95% CI = [0.16, 0.28], P = 1.29×10^{-13}). Cultural and geographic distance did not show
322 significant unique contribution to semantic variations (culture: $\beta = 0.07$, 95% CI = [-0.01, 0.14], P =
323 0.10; geography: $\beta = 0.05$, 95% CI = [-0.03, 0.13], P = 0.24). Our focus on sensorimotor-related
324 influences led us to further investigate climate effects across semantic dimensions. Further analyses
325 revealed that climate contributed significant effects across 12 of the 13 semantic dimensions (FDR-
326 corrected $qs < 0.05$), with the exception of the shape dimension (q = 0.12; Figure 3c, right panel). The
327 climate effects were robust across multiple validation analyses, including those utilizing alternative
328 pretrained word-embedding data and different random effect structures controlling for non-
329 independence (see Supplementary Text S2, S3; Figure S4).
330 We further tested whether the observed cross-linguistic associations between semantic variation
331 and climate were specific to the neurocognitive semantic structure. Linear mixed regression models
332 were employed with climate and other semantic structures as regressors to predict neurocognitive
333 semantic variations and vice versa. Results in Table 1 indicated that the relationship between climate
334 and neurocognitive semantic structure remained significant even when controlling for distributional
335 and feature-based models. Specifically, climate maintained a significant association with
336 neurocognitive semantic structure after controlling for distributional global ($\beta = 0.03$, p = 0.02),
337 distributional local ($\beta = 0.11$, p < 0.001), and semantic ($\beta = 0.13$, p < 0.001) models. Conversely, when
338 predicting these alternative semantic structures while controlling for neurocognitive structure,
339 climate showed either weaker or non-significant associations (distributional global: $\beta = 0.03$, p = 0.005;
340 distributional local: $\beta = -0.02$, p = 0.37; feature norm: $\beta = -0.03$, p = 0.15). These findings suggest a
341 specific relationship between climate and neurocognitive semantic organization that cannot be fully
342 explained by other semantic representation frameworks.

343

344 <u>Study 2: Human participants' behavioral ratings in 8 languages</u>

345

346   To investigate whether the principles of commonalities and variations observed in language
347   records (Study 1) are reflected in language speakers' semantic behaviors, we conducted a study with
348   participants from 8 languages (a subset of 53 languages in Study 1) with broad coverage of geographic,
349   linguistic, and cultural diversity: Arabic (Egypt), Chinese (China), English (USA), Hindi (India), Japanese
350   (Japan), Korean (South Korea), Russian (Russia), and Spanish (Spain). We recruited a final sample of
351   253 participants from 58 city sites across these countries (sampling procedures and geographical
352   information are provided in Methods, Figure S6 and Table S5). Participants were asked to rate the
353   Swadesh concepts (N = 207, Table S6) on their associations with the 13 neurocognitive dimensions,
354   resulting in individual semantic spaces comprising 2,691 ratings per participant (207 Swadesh
355   concepts × 13 neurocognitive dimensions). We computed Pearson correlations between the rating
356   vectors (207 concepts × 13 dimensions) for each participant pair, resulting in an *intersubject*
357   *correlational matrix* (Figure 3d). The matrix showed a substantial semantic component shared across
358   participants (65.78%), with much smaller language-specific effects (4.2%), validating the commonality
359   of such neurocognitive semantic structures across languages (see Supplementary Text S4 for details).
360   *Behavioral variations associated with climate and cultural distances.* We first computed average
361   ratings for each concept-dimension pair within each language to create language-level semantic
362   representations. To assess the relationship between neurocognitive semantic space variation and
363   environmental variables, we collected macroenvironmental variables (identical to those in Study 1)
364   for each language and constructed language-level environmental RDMs for climate, culture,
365   geography, and linguistic history (Figure 3e). We also included a demographic RDM to account for
366   variations in participants' age, gender, education level, and socioeconomic status across language
367   groups.
368   Hierarchical regression revealed that, in addition to the explanatory power of demographic
369   distance (R^2 = 0.12), the four environmental variables collectively accounted for an incremental 47%
370   variance in the neurocognitive semantic structural variations (Spearman ρ = 0.74, P < 0.001). In
371   alignment with our analytical approach in Study 1, we performed analyses at the language level, with
372   all four environmental variables as simultaneous predictors and random intercepts for language
373   families to account for phylogenetic relationships. Beta estimation (Figure 3f) showed that climate
374   had unique effects on cross-language semantic variation (climate: β = 0.53, 95% CI = [0.26, 0.80], P =
375   0.0006). The other three variables showed no or negative effects (culture: β = -0.07, 95% CI = [-0.36,
376   0.25], P = 0.64; geography: β = -0.22, 95% CI = [-0.40, -0.04], P = 0.02; linguistic history: β = 0.13, 95%
377   CI = [-0.17, 0.39], P = 0.34). When analyzing each neurocognitive dimension separately (Figure 3f,
378   right panel), all dimensional variations continued to be significantly modulated by climate (FDR-
379   corrected *q*s < 0.05). To examine whether these climate effects extend beyond language-level
380   variation to individual semantic representations, we conducted supplementary analyses while
381   controlling for non-independence (see Supplementary Text S3). These analyses confirmed that
382   climate effects remain robust across different random effect structures and are observable at both
383   language and individual participant levels.
384
385   Study 3: Human participants' brain activity patterns in 45 languages
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387   To investigate whether the principles of commonalities and variations observed in language
388   records (Study 1) are reflected in language speakers' neural responses during language
389   comprehension, we analyzed a multi-language functional magnetic resonance imaging (fMRI) dataset

comprising 86 individuals recruited from the United States, whose native languages spanned 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. Following our consistent analytical approach across studies, we aggregated individual neural responses at the language level. We first investigated whether neural activity patterns in these regions reflected cross-language alignment in the 13-neurocognitive-dimensional semantic space (based on embedding data in Study 1; Figure 3a). To this end, for overlapping language samples in two studies (65 participants, 33 languages; Figure 4b), we computed language-level neural RDMs for each brain region by averaging t-value maps from speakers of the same language. We then used linear mixed regression models to assess the relationships between these neural RDMs and the 13-dimensional neurocognitive semantic model RDMs from Study 1, while including random intercepts for language families to account for the phylogenetic structure. Significant beta coefficients were found only in the right anterior temporal lobe (ATL; $\beta = 0.44$, 95% CI = [0.17, 0.71], FDR-corrected $q = 0.016$). 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 the r-ATL when processing language. Given the right ATL's role in semantic processing and the significant relationships with our semantic space representation, we identified this region as our primary region of interest for subsequent analyses (Figure 4c). We first found that r-ATL showed a certain degree of cross-language commonalities, validating our commonality results (Supplementary Text S4).

Neural variations associated with climate and cultural distances. To maintain analytical consistency with Studies 1 and 2, we constructed language-level environmental RDMs based on climate, cultural, geographic, and linguistic history distances (Figure 4c; see Methods), analyzing 25 languages for which all environmental measures were available. Linear mixed regression models revealed that climate distance significantly predicted neural pattern dissimilarities in the r-ATL ($\beta = 0.12$, 95% CI [0.04, 0.22], P = 0.01), while the other three distances did not reach significance (all Ps > 0.05). To assess robustness, we conducted additional analyses with alternative random effect structures (see Supplementary Text S3), which consistently showed that climate effects remain significant across different model specifications.

Importantly, when using environmental RDMs to predict the r-ATL's neural activity during non-linguistic tasks (e.g., Spatial Working Memory -- Hard vs Easy; Math -- Hard vs Easy), the climate effects were no longer significant, suggesting that these effects are unique to language-related processing (Supplementary Text S5; Figure S7). To further characterize the relationship between semantic and climate effects in the r-ATL, we conducted a commonality analysis to partition the r-ATL variance explained by different components (Figure 4c, right panel). This analysis revealed significant unique contributions from both semantic factors (6.26%, 95% CI [1%, 37.46%]) and climate factors (55.58%, 95% CI [16.83%, 85.80%]), as well as substantial common variance shared between climate and semantic effects (38.20%, 95% CI [14.75%, 48.30%]). The significant common variance suggests that climate effects on neural activities in the r-ATL partially reflect semantically related neural activation patterns.

433   Summary of the variation analyses results: Cross-language variations on the 13-neurocognitive-
434   dimension structure obtained from language computation data (Study 1), human behavior rating data
435   (Study 2), and multi-language fMRI data (Study 3), were all significantly predicted by climate, the
436   effects of which were also robust across all validation analyses (see Table 2). Our neural findings in
437   Study 3 revealed that climate-related semantic variations were specifically associated with activity
438   patterns in the right ATL, a critical region for semantic processing, with a substantial portion of climate
439   effects reflecting semantically related neural activation patterns.

440

441   **Exploratory analyses on the associative patterns between climate and semantic space**

442

443   Having identified that climate has robust and unique effects on variations in semantic structures
444   across large text models (Study 1b), subjective ratings (Study 2), and brain activity patterns (Study 3),
445   we aimed to elucidate the semantic profiles that are associated with the major climate groups. We
446   carried out the following analyses based on the embedding data from Study 1 given that this study
447   covers the largest language sample and concept set. We performed a PCA on climate data consisting
448   of 19 biologically relevant climate variables related to temperature and precipitation across 53
449   languages. The results revealed two primary climate-related principal components (PCs): Climate-PC1,
450   accounting for 42.3% of the variation, and Climate-PC2, accounting for 30% (Figure 5a). The
451   contributions of specific climate variables to these PCs (Table S7) led us to characterize the Climate
452   PC1 as representing "cold/temperate vs. tropical" climates and the Climate PC2 as representing
453   "oceanic vs. continental" climates (more precipitation and low seasonality vs. less precipitation and
454   high seasonality).
455   To project the semantic space along each PC axis, we scaled the semantic space for each language
456   and multiplied it by their loadings on the two climate PCs, resulting in semantic spaces along the
457   Climate PC1 and Climate PC2 axes (Figure 5b). Higher values along a particular direction of PCs
458   indicate that the given climate type tends to have stronger semantic relations. The associated
459   semantic space for Climate PC1 and Climate PC2 is visualized for each concept (Figure S8) and
460   summarized by domains (Figure 5b). For Climate PC1 (cold/temperate vs. tropical) dichotomy,
461   concepts in general tend to exhibit higher intensity on emotional and sensorimotor dimensions
462   (touch, motor, shape, color) in the cold/temperate zones and higher intensity on social-cognitive
463   (social, space, number, cognition) and smell dimensions in tropical zones. For Climate PC2 (oceanic
464   vs. continental) dichotomy, concepts tend to exhibit higher intensity on the smell, cognition, and time
465   dimensions in oceanic zones and higher intensity on the social and sound dimensions in continental
466   zones.
467   One data pattern emerged from this visualization (Figure 5b): The dimensional difference
468   patterns associated with climate groups are overall coherent across various concepts (and concept
469   domains). For Climate PC1, cold/temperate climate is associated with higher loading on emotion (and
470   sensorimotor) not only for specific concepts relating to temperature, such as "sun" or "warm", and
471   tropical climate is associated with higher loading on olfactory not only for "flower" and on social not
472   only for "father", but for all domains of concepts in general. This pattern of association with
473   dimensions instead of concept domains is also present for Climate PC2, although less clear-cut (see
474   examples in Figure 5b, lower panel).

475
476

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 local/global 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.

Stronger universality of neurocognitive model compared to control models

Previous studies on cross-language semantic alignments have focused on the degree of 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 (Lewis et al., 2023; Thompson et al., 2020) 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 distributional (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" (Italian data, Bottini et al., 2020; US data, Martin et al., 1995; Chinese data, Wang et al., 2020). Note that compared to Lewis et al. (2023), which also studied distributional models and showed that global distribution space (excluding within-domain neighbors as anchors) showed less universality compared to local space (within-domain neighbors as anchors), our analyses of global

13

521 distribution space included all word relationships in the vocabulary space (i.e., grand global), and
522 showed greater universality. These results, when considered together, indicate that preserving
523 domain structure is important in capturing cross-linguistic semantic universals. These neurocognitive
524 dimensions, gleaned from neuroimaging studies based on a few languages (see Table S1), capture
525 similarities across much larger language samples (53 languages, spanning 10 language families
526 including Indo-European, Afro-Asiatic, and Dravidian), most of which have not been studied in
527 cognitive neuroscience (e.g., Breton, Bashkir, and Tatar). Importantly, the cross-language similarity for
528 word semantic representations computed this way is significantly greater than those computed based
529 on relational structures with global or local neighboring words, or with psycholinguistic features that
530 were not as neurobiologically salient. The advantage of the neurocognitive model over these control
531 models on the same dataset is not readily explained by potential limitations of the language samples
532 (e.g., all Eurasia). Further confidence is gained from the results showing that the shared
533 neurocognitive representation of the 53 languages significantly predicts colexification network
534 properties across 2,681 languages. These results are readily explained by the assumption that these
535 neurobiological structures scaffold a universal semantic representation regardless of the types of
536 languages spoken.

537

538 **Variations along the neurocognitive semantic structure associate with climate**

539

540 Regarding variations, aligning with the observations of the cultural/linguistic effects on concept-
541 level alignment (Lewis et al., 2023; Thompson et al., 2020), we found that deviations along the
542 semantic structures were significantly associated with linguistic similarity in Study 1 and cultural
543 similarity when using another embedding model (see Supplementary Text S2), suggesting that
544 sociocultural processes (via word borrowing, cultural communications) could also help promote
545 alignment on such semantic structure. The key novel finding is the robust unique effect of climate
546 beyond these variables in explaining semantic variations across the word embedding model, human
547 semantic behavior, and brain data.
548 Given the universal neural mechanism of deriving semantic representation from multimodal
549 sensorimotor experiences (respecting core knowledge domains), environmental variables could have
550 an effect on sensory experiences and/or related bodily functions, which in turn would affect semantic
551 representations. Climate is one such variable. Indeed, climate properties such as temperature and
552 precipitation contribute to human perceptual environments such as sun color, landscape variations,
553 and interaction patterns among local populations, plants, and animals. Recent evidence has even
554 suggested that oxygen concentration and/or other environmental factors associated with high
555 altitude affect color perception, which is assumed to be driven by different oxygen consumption
556 sensitivities of different cones in the retina (Kobrick, 1970; Wang et al., 2019). Speakers who reside
557 in distant locations but experience similar climates are more likely to share similar sensory/perceptual
558 inputs and thus more similar semantic representations. Notably, our results from both word
559 embedding and behavioral rating experiments demonstrate that climate exerts a robust effect across
560 all semantic dimensions, encompassing not only sensorimotor properties but also higher-order
561 domains such as mental-cognition, time, space, number, social, and emotion (Figures 3c and 3f).
562 Sensorimotor dimensions are expected to be directly shaped by environmental inputs. While higher-
563 order cognitive dimensions are further abstracted from immediate perceptual input, they arguably
564 remain partially grounded in sensorimotor experience (Sigismondi et al., 2024). These findings are

565 consistent with prior evidence that environmental conditions can modulate temporal perception (Li
566 et al., 2022), and that climate-linked subsistence patterns shape social behaviors and emotional
567 tendencies (Talhelm et al., 2014; Van de Vliert, 2013), and they clearly invite further investigations
568 into the underlying neurocognitive mechanisms. This broad dimensional effect is also in line with our
569 intriguing observation of climate-brain activity associations in the r-ATL in the human brain. Note that
570 we analyzed brain activity for the "intact vs. degraded" contrast, which captures broad linguistic
571 processes including, but not limited to, semantics. Regarding the ATLs' role in language processing,
572 accumulating research has established them as key regions for processing higher-order semantics,
573 binding the distributed semantic dimensional representations and word relational structures in
574 language (see reviews in Bi, 2021; Lambon-Ralph et al., 2017; Miyashita, 2019). Indeed, the
575 commonality analyses revealed significant shared components between climate and semantics,
576 linking ecological variables and language neural processing that converges with our behavioral and
577 computational findings. We do not exclude other potential language processes that may also mediate
578 the climate-ATL association -- our commonality analysis indeed also revealed significant variance
579 shared by climate and neural activities that is not shared with semantics.

580　　Our findings have broad implications for understanding cultural evolution. Previous research has
581 emphasized the broad impacts of ecological variables (e.g., climate) on human sociocultural
582 behaviors (Van de Vliert, 2020; Wormley et al., 2023). Given that information is ultimately processed
583 by the internal models of the human brain for behavior, the variations along the neurobiological
584 semantic structures may serve as a cognitive mechanism underlying such processes. Indeed, we
585 identified specific semantic profiles that were associated with different major climate groups (Figure
586 5b). For instance, the social semantic dimension loads more strongly in languages of tropical regions,
587 which may help explain the previous reports about higher temperatures associating with stronger
588 collectivism (Van de Vliert, 2020). However, evidence regarding climate's influence on within-
589 dimension semantic variations shows mixed patterns - Brown (2005)'s findings on arm-hand lexical
590 distinctions in colder regions support climate-based accounts, while spatial reference frame
591 variations (absolute vs. relative) may be more influenced by a complex set of factors rather than by a
592 single factor such as climate (Majid et al., 2004). More generally, having identified the robust
593 association between climate and a central cognitive component — semantics, future studies
594 elucidating the detailed neurocognitive mechanisms would be critical for understanding the intricate
595 interplay between our living environment and diverse human behaviors, especially in the era of
596 profound climate change.

597

Limitations

599　　A few caveats and future directions warrant discussion. First, our selection of dimensions in the
600 neurocognitive dimensional structure, while based on existing positive findings regarding cognitive
601 neural semantic organizations, may not be exhaustive or entirely independent. Second, true
602 translation equivalence across languages is impalpable given theoretical and empirical considerations.
603 We tested words from the NorthEuraLex database, which contains dictionary-compiled translations.
604 As Dellert et al. (2020) noted, many languages make lexical distinctions absent in English (e.g.,
605 differentiating "air" as a breathable substance versus a space for flight), and these mappings lack
606 extensive native speaker validation. Despite these inherent limitations, our study focuses on the
607 underlying principles governing such cross-linguistic (mis)alignments. Third, each method has
608 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 at the language level and much smaller in the human 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. Future studies should employ tasks specifically designed to isolate semantic processing across diverse languages to more precisely characterize climate-semantic neural relationships. 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 the three studies, they have all undergone varying degrees of modernization. This may lead to an overestimation of the climate effects and an underestimation of the effects of cultural and linguistic factors on semantic structures, which warrants further investigation. Future research with more globally representative language samples is necessary to validate the generalizability of our findings.

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

<u>Study 1: Language computational study using word embedding data in 53 languages</u>

<u>Language samples and concept list</u>: 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 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 (see below). 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 the same results. Detailed language information can be found in Table S2, and the distribution of concept numbers for each language is illustrated in Figure S9.

<u>Multi-language pretrained word embedding model</u>: 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 hundreds of millions to billions 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). FastText represents words as a combination of whole-word and subword (character n-gram) embeddings, which allows for better handling of morphologically rich languages and out-of-vocabulary words (Bojanowski et al., 2017). 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 an anchor word approach (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: distributional 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 feature 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 into 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

697 vector and the vectors of anchor words for each dimension to obtain a 13-dimensional vector as the
698 neurocognitive semantic representation. Using the original anchor concepts from Binder et al. (2016),
699 which were selected by English speakers, yielded the same result patterns.

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

710

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

715   *Inter-language correlation analysis.* For each semantic representation model, we calculated the
716 Pearson correlation coefficient (r) between the semantic representations of each language pair for all
717 1,016 concepts. The resulting inter-language correlation (ILC) was then Fisher's r-to-Z transformed
718 and averaged across concepts. To compare the ILCs between different types of theoretical semantic
719 representations, we employed the Wilcoxon signed-rank test (two-sided) for paired samples.

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

727

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

737   We conducted separate analyses using colexification networks derived from: a) The entire CLICS
738 language sample (N = 2,681); b) A subset of non-Eurasian languages from the CLICS database. For 165
739 of the 204 concepts used in the pretrained embedding analyses, we extracted the following network
740 properties from the CLICS database: edge weight, weighted common neighbors, and community

741 structures based on Louvain and Infomap algorithms. These measures capture first-order, second-
742 order, and global information in the network, respectively, and are widely used to quantify semantic
743 similarity across languages (Fu et al., 2023; Jackson et al., 2019; Tjuka et al., 2024). We computed an
744 overall pairwise similarity score as the average of these four metrics and then correlated these
745 network similarities with the neurocognitive semantic relations from the 53 languages in our
746 embedding data using Spearman correlation. The correlations were averaged across the 53 languages
747 to obtain a mean correlation for each network (full sample and non-Eurasian subset). The statistical
748 confidence of the neurocognitive models' predictability for colexification network properties was
749 established by comparing the model's Spearman correlation coefficients with the distribution of
750 correlation coefficients from the statistical control models (N = 1,000 times).

751

752 Prediction of inter-language semantic variations: To understand what environmental factors may
753 account for the variations in the universal semantic structure, we carried out representational
754 similarity analysis (RSA) between inter-language semantic variation and the distances of the four
755 salient ecological variables, including the geography, climate, linguistic history, and culture.

756 *Environmental variables*. We obtained pairwise distances on these four environmental variables
757 based on the languages' coordinates provided by Glottolog 4.6 (Hammarström et al., 2022). The
758 geographic distances were calculated as the geodesic distances between the locations of languages
759 on the Earth's surface. The climate distances were calculated as the scaled Euclidean distance based
760 on the estimates of 19 bioclimate variables from WorldClim (Fick & Hijmans, 2017; see Table S7 for
761 the full list). The 19 bioclimate variables were derived from the monthly temperature and
762 precipitation, which are often used in species distribution and related ecological modeling. The
763 distances of linguistic history were estimated based on cognates of the NorthEuralex wordlist, using
764 LingPy (List & Forkel, 2023) with the LexStat method (List, 2014). The cultural distances were retrieved
765 from Thompson et al. (2020), which were calculated based on the eco-cultural traits in the D-place
766 dataset (Kirby et al., 2016), including societies' housing, labor institutions, marriages, and political
767 systems.

768 *Representational similarity analysis*. The inter-language RDMs were first constructed for semantic
769 variations and for each environmental variable. The semantic RDM was constructed by computing
770 the distance (i.e., 1 − Pearson correlation, with Fisher's r-to-Z transformed) of averaged concepts'
771 neurocognitive semantic vectors between language samples. After obtaining these inter-language
772 RDMs, we performed nonparametric Spearman correlations for their raw associations and built
773 multiple regression models to estimate how the semantic variations across languages could be
774 explained by the environmental variables. Specifically, we tested the association between the lower
775 triangle of the semantic representational dissimilarity matrix (RDM) across languages and the lower
776 triangle of RDMs for each or composite of these environmental variables (excluding the main
777 diagonal elements). The linear mixed regression model was further conducted to estimate the fixed
778 effects of each environmental variable with a crossed random-effects structure that nested language
779 pairs within language families considered, to account for potential non-independent language
780 sampling (Chen et al., 2017; Thompson et al., 2020). The model can be formally expressed as:

781

782 $$Semantic\_Distance_{ij} = \beta_0 + \beta_1 Climate_{ij} + \beta_2 Culture_{ij} + \beta_3 Geography_{ij} +$$
783 $$\beta_4 Linguistic\_History_{ij} + (1 \mid Family_i) + (1 \mid Family_j) + \varepsilon_{ij}$$ (1)

784

785   , where i and j index the language pairs, β_0 represents the intercept, β_1 through β_4 represent the
786   fixed effects for each environmental variable, $(1|Family_i)$ and $(1|Family_j)$ represent the random
787   intercepts for the language families of languages i and j respectively, and ε_{ij} represents the residual
788   error term (see Supplementary Text S3 for details and other ways to control non-independence).
789   Effects of environmental factors on cross-language semantic variations at the single dimension level
790   were also assessed through linear mixed regression models.
791
792   **Study 2: Human participants' behavioral ratings in 8 languages**
793
794   Participants: We recruited a diverse sample of 272 online participants from 58 city sites across 8
795   countries, representing distinct languages: Arabic (Egypt), Chinese (China), English (USA), Hindi (India),
796   Japanese (Japan), Korean (South Korea), Russian (Russia), and Spanish (Spain). Participants were
797   recruited through the Appen crowdsourcing platform (http://www.appen.com). All participants were
798   confirmed to be native speakers residing in their respective targeted sites. To ensure geographical
799   diversity while minimizing intercorrelations among environmental variables of interest, we
800   strategically selected 6-8 geographically dispersed sites within each country (Figure S6; Table S5). To
801   ensure data quality, we implemented a stringent inclusion criterion. Participants whose rating vector
802   correlated less than 0.5 with the averaged group vector within their respective language were
803   excluded from the main analyses. This resulted in the exclusion of 19 participants. The final sample
804   size was 253 participants, with a balanced distribution of 30 to 34 participants per country. This study
805   was approved by the Institutional Review Board State of the Key Laboratory of Cognitive
806   Neuroscience and Learning, Beijing Normal University.
807
808   Concept list: For this study, we used the Swadesh 207-Word list, which has been extensively studied
809   in historical and comparative linguistics and is considered to represent the core basic vocabulary of
810   human languages (Swadesh, 1952). The 207 words also sufficiently overlapped with the NEL concept
811   list used in Study 1. To obtain translated word forms of these concepts across our target languages,
812   we sourced initial word forms from the PanLex Swadesh database (Kamholz et al., 2014) and asked
813   professional translators to review them. In cases where PanLex provided multiple word forms for a
814   single concept, our translators were instructed to select the most commonly used ones. To mitigate
815   potential ambiguity, particularly for polysemous words, we accompanied them with contextual
816   specifications (e.g., lie (as in a bed)). The final word forms are provided in Table S6.
817
818   Rating instructions: To evaluate the 13-dimensional neurocognitive semantic structures, participants
819   were instructed to rate concepts on the extent of association with specific dimensions. Our approach
820   was adapted from Binder et al. (2016), providing some forms of association for each dimension (e.g.,
821   for color, the association could be "This word refers to something that has a characteristic color (e.g.,
822   eggplant)", "This word describes the change in color (e.g., fade)", or "this word directly refers to a
823   particular color (e.g., red)"). To support participants' understanding, we included example words with
824   high and low loadings from Binder et al.'s questionnaire. To mitigate potential cross-cultural biases,
825   we excluded example words with below-average frequency based on word frequency data in Binder
826   et al. (2016) and example words that could introduce cultural biases. The English rating instructions
827   were translated into 7 other languages using multi-proofreading processes (Supplementary Text S6).

20

828 The rating instructions for each language can be found at the link
829 (https://osf.io/suyeb/?view_only=c0ca6847b89d4257807ee342463ac6b8).
830
831 Online rating procedures: Participants completed a prescreening process followed by three sessions
832 of the conceptual rating task.
833   *Prescreening*. To ensure native speaker selection, we employed a rigorous prescreening process
834 comprising self-reports and a 5-minute audio transcription test in the target language. We collected
835 detailed language background and demographic information, including age, gender, education level,
836 ethnicity, subjective socioeconomic status (SES; Adler et al., 2000), second language proficiency,
837 country of upbringing before age of 7, and current region of residence. Participants who were
838 nonnative speakers, failed the transcription test, had lived in a foreign country before the age of 7, or
839 were currently residing in foreign countries were not invited to the rating task. Moreover, those who
840 self-reported high proficiency in a second language (5 on a 5-point Likert scale, indicating "upper
841 intermediate and above") were also excluded. For Indian participants, criteria were adjusted due to
842 the country's multilingual nature, excluding only those with high proficiency in languages of interest
843 (e.g., English).
844   *Rating Task.* Eligible participants completed a rating task comprising three 50-minute sessions.
845 Each session involved rating approximately 70 words on 13 neurocognitive dimensions. The 207
846 concepts were pseudorandomly shuffled into 30 wordlists, which were then randomly assigned
847 across the three sessions. To ensure quality control during the process, three catch trials using high-
848 loading examples from the instructions were randomly inserted into each wordlist. The task
849 automatically terminated if erroneous (low) ratings were detected on control questions. Pearson
850 correlations were computed between each participant's rating vector and the averaged group vector
851 within each language. Participants with correlations below 0.5 were excluded from further analysis.
852 The final sample consisted of 253 participants. Analyses including all participants yielded similar
853 results.
854
855 Prediction of cross-language speakers' semantic variations: An inter-subject correlation matrix was
856 constructed by calculating Pearson correlation coefficients between each subject pair's ratings on 207
857 concepts across 13 dimensions (2,691 ratings per subject). We first analyzed the variance components
858 shared across individuals (universal), across languages (language-specific), and individual errors to
859 validate the commonality results (see Supplementary Text S4). To investigate the explanatory power
860 of macro environmental variables in understanding cross-language (neurocognitive) semantic
861 variations, we then shifted our analysis to the language level and employed RSA to predict language-
862 level semantic variations using the distance of the four environmental variables, including climate,
863 geography, linguistic history, and culture.
864   *Environmental variables*. We obtained environmental variables for each language by aggregating
865 information from participants' geographic locations. Specifically, we first collected city/county
866 location data from all participants within each language group. The site-level geographic coordinates
867 were obtained using the Bing Maps API (https://www.bingmapsportal.com/). For each language, we
868 then calculated the average coordinates to represent its geographic center. The climate profile for
869 each language was derived by extracting the 19 bioclimate variables from WorldClim (Fick & Hijmans,
870 2017) at these averaged coordinates. The geographic distances between languages were calculated
871 as the geodesic distances between these averaged coordinates. The linguistic history and cultural

872 distances were taken from the language/country level distance measurements from Study 1.
873 Additionally, we constructed a measure of demographic distances based on scaled Euclidean
874 distances to account for potential confounds (age, gender, education level, and SES) between
875 language groups.

876 *Representational similarity analysis*. For language-level analysis, we first computed average
877 ratings for each concept-dimension pair within each language to create language-level semantic
878 representations. The semantic RDM was constructed by computing the distance (1 - Pearson
879 correlation, with Fisher's r-to-Z transformed) between these language-level semantic representations.
880 We then constructed language-level environmental RDMs for climate, culture, geography, and
881 linguistic history, as well as a demographic RDM.

882 We first assessed raw association patterns between the semantic RDM and environmental RDMs
883 using nonparametric Spearman correlations. We then conducted hierarchical regression with
884 demographic distance entered as the first step, followed by the four environmental variables in the
885 second step to evaluate their collective contribution beyond demographic differences in explaining
886 semantic variations. Following the same procedures as in Study 1, we conducted linear mixed
887 regression models to estimate the unique fixed effects of each environmental variable while
888 controlling for the others. This model included all environmental variables as simultaneous predictors
889 with a random effects structure that included random intercepts for language families to account for
890 phylogenetic relationships.

$$Semantic\_Distance_{ij} = \beta_0 + \beta_1 Climate_{ij} + \beta_2 Culture_{ij} + \beta_3 Geography_{ij} + \beta_4 Linguistic\_History_{ij} + (1 \mid Family_i) + (1 \mid Family_j) + \varepsilon_{ij} \tag{2}$$

895 Effects of environmental factors on cross-language semantic variations at the single dimension
896 level were also assessed.

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

900 <u>fMRI dataset:</u> This study utilized an open-access multi-language fMRI dataset (Malik-Moraleda et al.,
901 2022) available at the OSF repository (https://osf.io/cw89s). The dataset comprises neural activity
902 measurements during a language comprehension task performed by 86 native speakers across 45
903 languages from 12 language families. Eighty-six participants (43 males; age range: 19-45 years) were
904 recruited from Boston, the United States. All participants were proficient in English in addition to their
905 native language. Participants underwent a passive listening task during fMRI scanning. They were
906 presented with auditory stimuli consisting of passages from "Alice in Wonderland" translated into
907 their native languages. The stimuli were presented in two conditions: intact native-language
908 condition and acoustically degraded-language condition (control condition). This contrast between
909 the two conditions is commonly used to obtain neural activities that are related to high-level language
910 processing, including semantics. We obtained the preprocessed whole-brain contrast maps (t-value
911 maps comparing intact native-language and acoustically degraded-language conditions) for all 86
912 participants from the OSF repository for our analysis. Detailed information on subject characteristics,
913 imaging acquisition procedures, task designs, data preprocessing and first-level modeling are referred
914 to Malik-Moraleda et al. (2022).

Prediction of cross-language speakers' neural variations: We investigated whether environmental effects were reflected in cross-language speakers' neural activity patterns during language processing using RSA methods. Our analysis proceeded in the following steps:

Identification of brain regions encoding cross-language semantic alignment (ROI Identification): For each of the 12 language-responsive regions, we first aggregated individual neural responses at the language level by averaging t-value maps from speakers of the same language. We then assessed whether neural activity patterns in these regions reflected cross-language alignment in the 13-neurocognitive-dimensional semantic space derived from Study 1. For this analysis, we constructed neural RDMs for each brain region and compared them with semantic RDMs using a linear mixed regression model that included random intercepts for language families:

$$Neural\_Distance_{ij} = \beta_0 + \beta_1 Semantic\_Distance_{ij} + (1 \mid Family_i) + (1 \mid Family_j) + \varepsilon_{ij} \quad (3)$$

Construction of environmental variables. We obtained environmental variables for each language based on Glottolog 4.6 coordinates (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 history distances were obtained from lang2vec (https://github.com/antonisa/lang2vec), which calculates the distance between two languages by counting the number of upward steps required on the tree until both languages converge at a common node, circumventing the need for cognate calculations on specific wordlists.

Representational similarity analysis. To assess environmental influences on neural activity patterns in the r-ATL, we constructed language-level environmental RDMs for climate, culture, geography, and linguistic history. We then used a linear mixed regression model to test whether these environmental variables predicted neural pattern dissimilarities:

$$Neural\_Distance_{ij} = \beta_0 + \beta_1 Climate_{ij} + \beta_2 Culture_{ij} + \beta_3 Geography_{ij} + \beta_4 Linguistic\_History_{ij} + (1 \mid Family_i) + (1 \mid Family_j) + \varepsilon_{ij} \quad (4)$$

Relationship between semantic and environmental effects. To further characterize the relationship between neural activity, semantic and environmental variations, we conducted a commonality analysis. This analysis partitioned the variance in neural pattern dissimilarities into components uniquely attributable to semantic factors, uniquely attributable to environmental factors, and shared between them. This analysis provided insight into how environmental and semantic factors might jointly influence neural representations during language processing.

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

960   YB, ZF, and XW wrote the paper.

961   **Competing Interests:** The authors declare no competing interests.

965   **Data and materials availability:** Data and codes used in this study were deposited to OSF

966   https://osf.io/suyeb/?view_only=c0ca6847b89d4257807ee342463ac6b8 .

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Figures and Tables
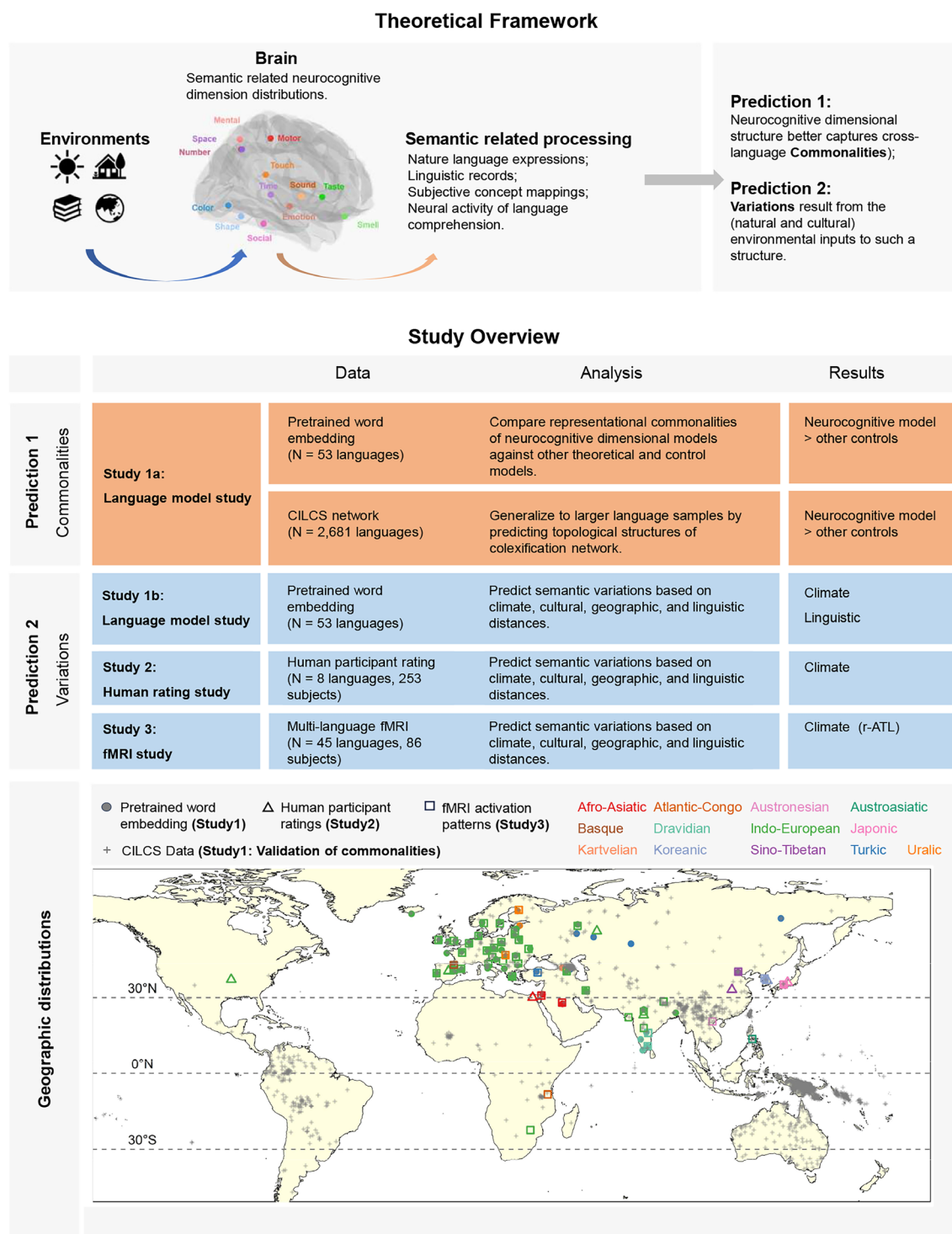
Figure 1. Theoretical framework and study overview. The core research question investigates the principles organizing cross-language semantic space by examining commonalities and variations observed in various types of data: natural language expressions, linguistic records, subjective concept mappings, 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 a 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.
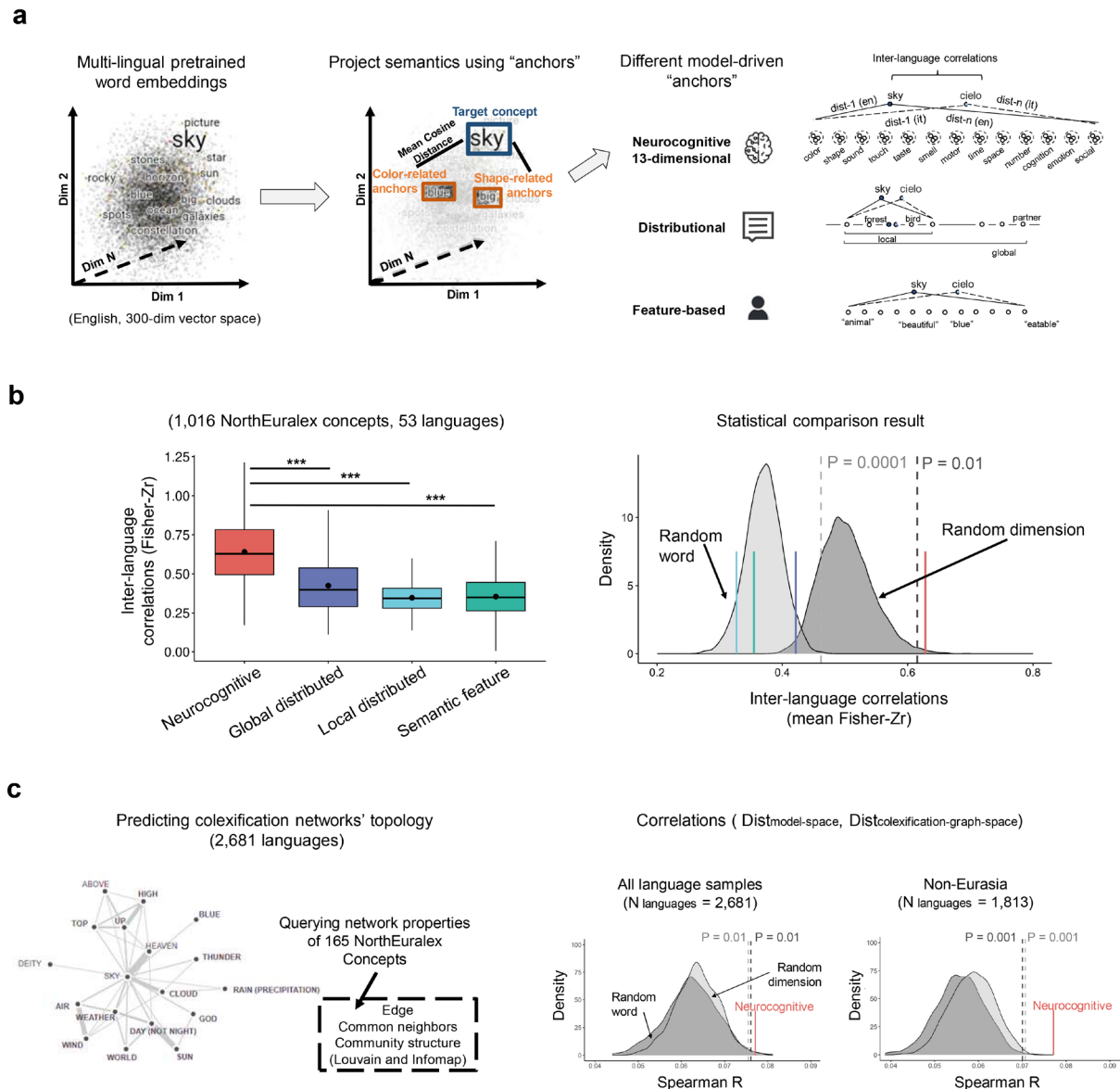
Figure 2. Commonality of the neurocognitive semantic structure across languages using language computational analysis (Study 1a). a. Semantic construction methods in the pretrained word embedding data analyses. Pretrained 300-dimensional word embedding data from 53 languages from 10 language families 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 those of the two control models (Ps < 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 (Ps < 0.01, red line) is at the upper bound of the random model distributions, demonstrating robust cross-linguistic generalizability.
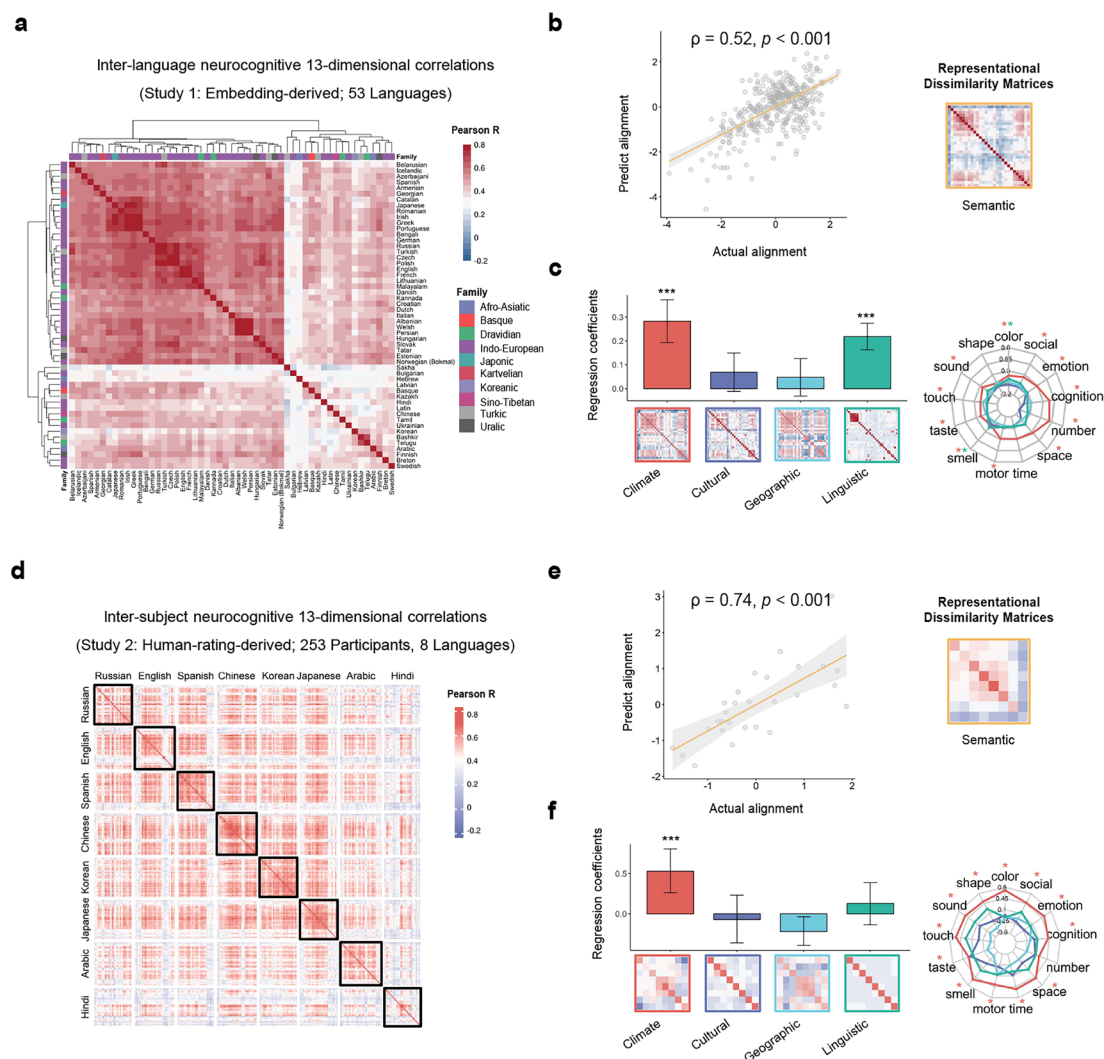
Figure 3. Environmental predictors of neurocognitive semantic variations in word embedding data (53 languages; Study 1b) and human rating data (253 participants, 8 languages; Study 2). a. Inter-language correlation matrix of 53 languages based on the 13 neurocognitive dimensional structure. The dendrogram shows the hierarchical clustering of languages by correlation distances, with languages color-coded according to language family. **b.** Scatter plot showing the relationship between actual and predicted semantic alignment based on environmental RDMs (climate, linguistic history, geography, and culture). **c.** Left panel: Linear mixed regression models predicting cross-language semantic variations with environmental RDMs. Standardized regression coefficients for each factor are shown, with the factor RDM displayed below each bar. Right panel: Radar plot displaying standardized beta coefficients from regression models for each of the 13 neurocognitive dimensions across environmental variables. **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.** Scatter plot showing the relationship between actual and predicted semantic alignment values based on environmental variables. **f.** Left panel: Linear mixed regression models predicting the inter-subject language 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. Right panel: Dimension-specific environmental effects. Radar plot displaying standardized beta coefficients from regression models for each of the 13 neurocognitive dimensions across environmental variables. Error bars represent 95% CIs. Significance levels: ***, P < 0.001; **, P < 0.01; *, P < 0.05.
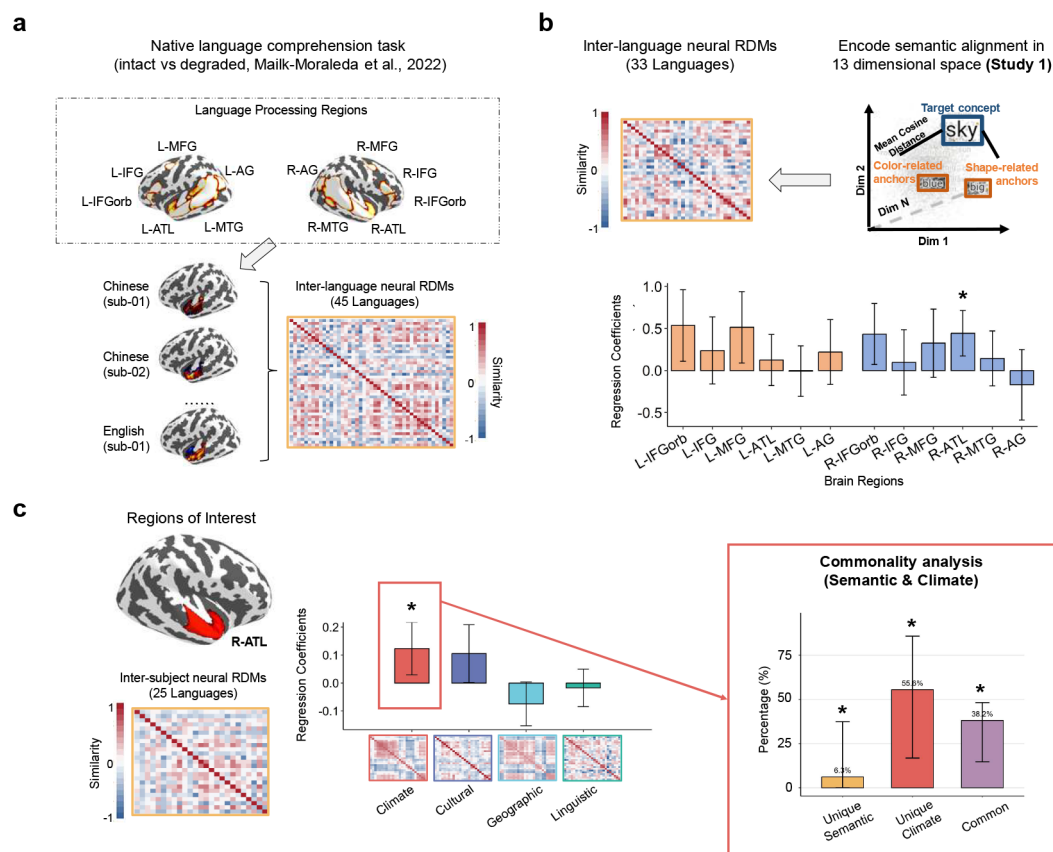
Figure 4. Neural correlates of environmental effects on language processing (Study 3). a. Methodology for constructing neural RDMs from 86 subjects across 45 languages within the high-level language processing network (Fedorenko et al., 2010). Inter-language neural RDMs were derived from the contrast between intact and degraded native language processing (Malik-Moraleda et al., 2022), with data averaged for each language. **b**. Linear mixed regression analysis at the language level, using semantic relation patterns (from the 13-neurocognitive dimensional space in Study 1) to predict cross-language neural variations. The bar plot depicts regression coefficients across all 12 brain regions. The right ATL is the only region showing significant beta values after multiple corrections (FDR-corrected $p < 0.05$), indicating that this region encodes cross-language semantic alignments in the 13-dimensional space derived in Study 1. **c**. Climate effects on neural activity patterns in the right ATL. Environmental factor RDMs were obtained for participants' native languages. The regression coefficient plot (left panel) illustrates significant climate effects in the right ATL. The commonality analysis (right panel) quantifies the proportion of variance explained by different components: unique semantic effects (6.26%, 95%CI [1%, 37.46%]), unique climate effects (55.58%, 95% CI [16.83%, 85.80%]) and common variance shared between climate and semantic factors (38.20%, 95% CI [14.75%, 48.30%]). The significant common variance indicates that climate effects on neural activities in the right ATL partially reflect semantically related neural activation patterns. 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. Error bars represent 95% CIs. Significance levels: * P < 0.05.
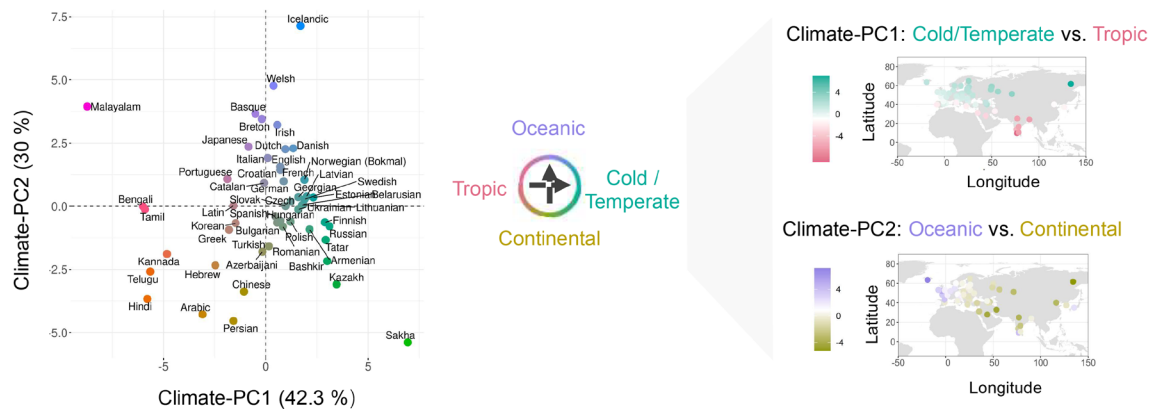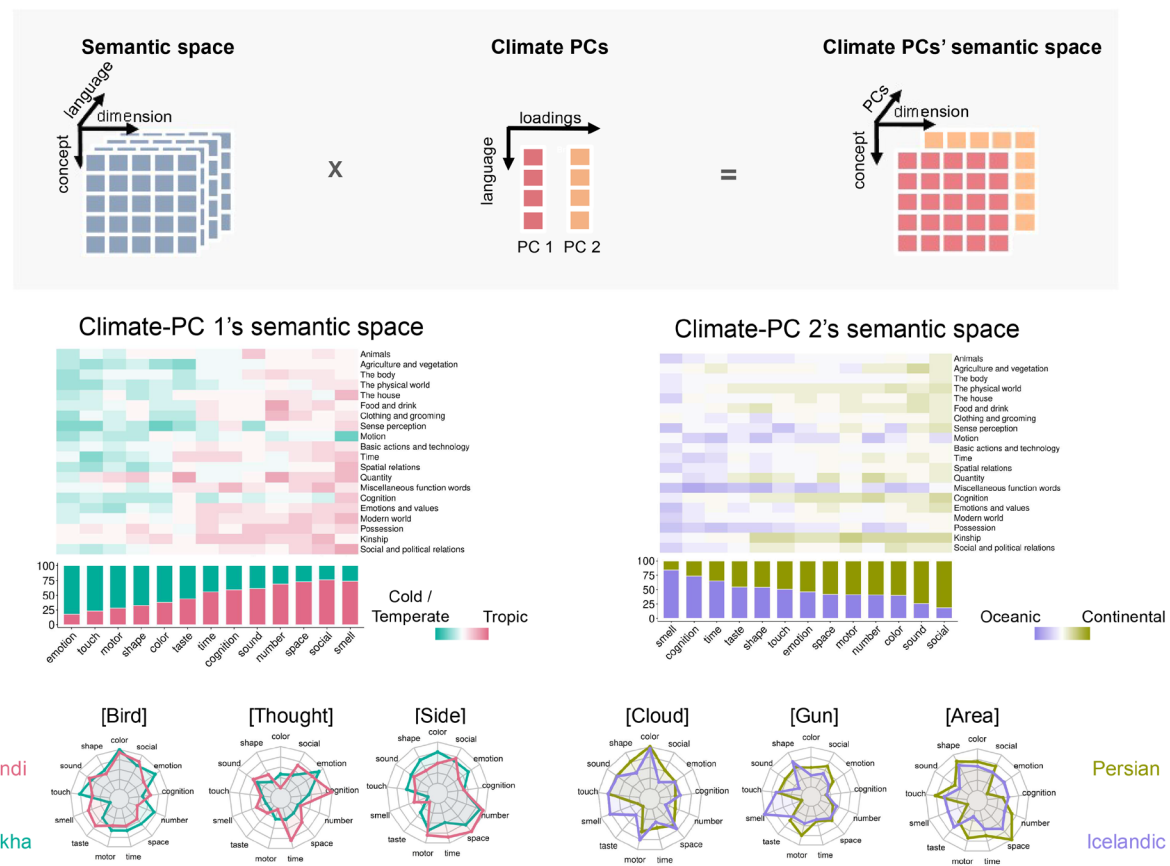
Figure 5. Semantic variation structures associated with different climate groups. **a.** Climate typology and distribution of 53 languages. PCA on the 19 climate variables of the geographic coordinates of 53 languages revealed that the first two principal components captured 72.3% of climate variations, 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.

Table 1. Unique effects of climate on different semantic structures

Model Type	Climate Effect (β)	95% Confidential Intervals
Model 1: Neurocognitive as DV		
Neurocognitive ~ Climate + Global Dist.	0.03*	[0.01, 0.05]
Neurocognitive ~ Climate + Local Dist.	0.11***	[0.09, 0.13]
Neurocognitive ~ Climate + Feature	0.13***	[0.10, 0.14]
Model 2: Alternative Models as DV		
Global Dist. ~ Climate + Neurocognitive	0.03***	[0.02, 0.06]
Local Dist. ~ Climate + Neurocognitive	-0.02	[-0.03, 0.01]
Feature ~ Climate + Neurocognitive	-0.03	[-0.04, 0.00]

Note: *** P < 0.001, ** P < 0.01, * P < 0.05; DV, dependence variable; Global Dist., global distributed model; Local Dist., local distributed model; Feature, semantic feature model; All models control for random effects of language families; All variables were standardized.

Table 2. Standardized regression results for environmental predictors of semantic distance across four datasets

Data Types	Climate	Cultural	Geographic	Linguistic History
Word embedding data (wiki + CC)	0.28 (0.20, 0.37) $P = 1.50 \times 10^{-9}$***	0.07 (-0.01, 0.14) $P = 0.10$	0.05 (-0.03, 0.13) $P = 0.24$	0.22 (0.16, 0.28) $P = 1.29 \times 10^{-13}$***
Word embedding data (wiki + Subs)	0.44 (0.33, 0.58) $P = 1.39 \times 10^{-10}$***	0.22 (0.12, 0.33) $P = 4.64 \times 10^{-5}$***	-0.18 (-0.29, -0.06) $P = 0.002$**	0.28 (0.20, 0.35) $P = 7.86 \times 10^{-12}$***
Behavioral data	0.53 (0.26, 0.80) $P = 0.0006$***	-0.07 (-0.36, 0.25) $P = 0.64$	-0.22 (-0.40, -0.04) $P = 0.02$	0.13 (-0.17, 0.39) $P = 0.34$
Neural data (R-ATL)	0.12 (0.04, 0.22) $P = 0.01$*	0.11 (0.008, 0.21) $P = 0.047$*	-0.07 (-0.15, 0.002) $P = 0.06$	-0.02 (-0.08, 0.04) $P = 0.61$

Note: Values represent standardized beta coefficients with 95% confidence intervals in parentheses. Significance levels: *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$.