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Applying Latent Space Network Modeling to Compare Word Associations of School-Age Children and Adults

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Abstract

This study uses latent space network modeling to explore how the structure of the mental lexicon might change from middle childhood (ages 7 to 11 years) to young adulthood. English-speaking children and adults (N = 21 per group) completed a repeated word association task where they generated the first word that came to mind in response to a list of 48 cues (24 nouns, 24 verbs) repeated three times. We applied mixed-effects models to examine how response characteristics, derived from robust metrics (e.g., WordNet, BERT), varied by group and list repetition. Semantic and phonological distance between responses and cues increased over list repetitions. Adult responses exhibited stronger semantic (word embedding and taxonomic) similarities, while child responses showed stronger phonological relatedness. To evaluate factors associated with producing specific responses, we modeled the corpus using latent space networks. This confirmed a stronger influence of distributional statistics in adults and phonological relatedness in children.

Keywords: Latent space network modeling; vocabulary; word associations; distributional semantics

Introduction

There is a long tradition of conceptualizing the mental lexicon as an integrated network, with words serving as nodes and edges between words representing shared relations or associations (Collins & Quillian, 1969; Harris, 1954). Longstanding questions concern how words are organized within the lexical network and how its structure might change as individuals grow their vocabularies. To this end, researchers have examined how various types of word relations influence lexical processing, such as shared taxonomic (e.g., *cat* and *dog* are animals) and phonological characteristics (e.g., *cat* and *car* share onsets, *cat* and *hat* rhyme) and similarities in the distribution of co-occurring words in large language corpora (Landauer & Dumais, 1997; Liang, 2025). In addition to relational features, researchers have studied how word-level features like concreteness and age of acquisition may influence a word's centrality or position within a lexical network (Cox et al., 2025; Ding et al., 2017).

Interest in the impact of these features on lexical processing has led to the construction of robust metrics for quantifying relational and word-level features. Widely used examples are Word2Vec and BERT, which are language models that are trained on a vast corpora of text to derive similarity scores (Devlin et al., 2019; Mikolov et al., 2013). In other work focusing on word-level features, researchers have asked thousands of participants to judge words across dimensions such as their concreteness (Kuperman et al., 2012) or age of acquisition (Brysbaert et al., 2013), or use large corpuses of representative speech or text to derive reliable estimates of word frequency (Brysbaert & New, 2009; Lison & Tiedemann, 2016).

These same relational and word-level features have figured prominently in research on lexical development. From a young age, children are sensitive to phonological contrasts and mispronunciations (Berko & Brown, 1960; Von Holzen & Bergmann, 2021). Indeed some research suggests that phonological similarities may be more salient in early childhood than later in life (Cronin, 2002; Dewhurst & Robinson, 2004; Sheng & McGregor, 2010), and play a major role in structuring the mental lexicon as it develops in early childhood (Vitevitch, 2022). In studies of object categorization, young children seem to rely increasingly on abstract taxonomic similarities (paradigmatic associations) over thematic similarities (syntagmatic associations) as their vocabulary knowledge develops (Arias-Trejo & Plunkett, 2010; Gopnik & Meltzoff, 1987; Rämä et al., 2013). At the same time, continuous exposure to new vocabulary across myriad circumstances and communicative contexts may serve to reinforce syntagmatic associations and other statistical regularities in the language environment (Savic et al., 2023; Yu, 2008).

Use of Word Association Data in Network Modeling

Free word association tasks have gained popularity as a method for generating datasets for lexical network analysis (Kiss, 1968; De Denye & Storms, 2008). One of the main foci has been to characterize the endogenous structural properties of the resulting networks (Budel et al., 2023; Deyne et al., 2019), such as its density (i.e. the number of observed associations divided by the total number of possible associations), average length of the shortest path between any two nodes (words), and the propensity of nodes to cluster together. In general, networks generated from word associations tend to be sparse (i.e., many nodes do not share an edge) with short path lengths. Networks derived from the responses of different participant groups (e.g., adults vs. children) will tend to vary in size depending on the number of shared associations vs. unique responses. This makes it difficult to compare networks directly because statistics such as density or clustering are inherently correlated with network size. That is, as network size

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increases, density tends to decrease, and clustering of nodes tends to increase (Newman, 2006).

Additionally, researchers have begun to consider how exogenous features of words (e.g., age of acquisition) or pair-wise word similarities (e.g., distributional co-occurrence, phonological relatedness) influence network structure (Beckage & Colunga, 2019; Castro et al., 2020; Hills et al., 2009; Sailor, 2013; Stella et al., 2017). Efforts to incorporate the robust metrics of word-level features and word similarities in studies of word associations have tended to use traditional mixed-effects models to compare responses generated by different participant groups. For example, Brooks et al. (2017) used Latent Semantic Analysis (Landauer & Dumais, 1997) and Continuous Bag of Words (Mandera et al., 2017) to compute similarities between cue words and responses of children with or without a history of developmental language disorder, and found lower semantic relatedness of responses in the language impaired group.

While efforts to include lexical features into network modeling have increased, these efforts are largely limited to descriptive analyses. Gravelle and Brooks (2025) introduced latent space network models as an inferential modeling approach to explore the extent to which exogenous features predicted network structure (e.g., edge weights), using data drawn from word associations generated by groups of adults with below-average vs. above-average vocabulary knowledge. Latent space network models adopt a regression framework (Cranmer et al., 2020; Hoff et al., 2002), allowing us to estimate the relative importance of different exogenous (word-level features and pairwise similarities) and endogenous characteristics on network structure. In the context of word association data, the position of the nodes within the latent space represents the closeness of the words within the mental lexicon. Gravelle and Brooks (2025) found significant effects of word embedding and taxonomic similarity across both networks (i.e., derived from responses of adults with above-average vs. below-average vocabulary knowledge), underscoring the role of semantic relatedness in structuring word associations. In contrast, only the below-average network showed influences of phonological similarity on network structure.

Research Questions and Hypotheses

The present study used data from a repeated word association task to elucidate how different word-level features and pair-wise similarities influence the structure of the mental lexicon and how the prominence of these features changes from middle childhood to adulthood. We collected word associations from school-age children (ages 7 to 11 years) and young adults (ages 18 to 26 years) and examined how the quality of their responses varied over repetitions of the list of cue words. We predicted that adults would generate word associations with higher relatedness to the cues than children due to their having greater language exposure and vocabulary knowledge. Specifically, we expected that adult responses would have higher word embedding and taxonomic similarity to the cues than child responses. However, given the increased salience of phonological relations in childhood (Dewhurst & Robinson, 2004; Sheng & McGregor, 2010), we expected children to generate responses more similar in sound patterns to the cues than adults. With regard to list repetitions, we expect to see decreases in cue–response similarity as both children and adults access weaker associations at later repetitions. With regard to word-level features, we expected words with higher concreteness, earlier age of acquisition, and higher frequency to be more accessible and prominent in lexical networks, which might reflect a tendency for lexical networks to follow a preferential attachment growth pattern (Cox et al., 2025). The prominence of these features was expected to decrease across list repetitions as participants accessed weaker associations.

As a follow up to the more traditional mixed-effects models, we explored the feasibility of capturing influences of cue–response similarity and word-level characteristics using latent space network models, and compared the results to the traditional mixed-effect analysis for validation. In terms of network structure, we hypothesized that the latent space of the adult network would have greater clustering than the child network, as word meanings and associations become more specific and differentiated with development.

Method

Participants

School-age children (N = 21, 14 girls, 7 boys; mean age 9.5 years, SD = 1.3, *range* = 7–11) and young adults (N = 21, 13 women, 8 men; mean age 20.3 years, SD = 2.4, *range* = 18–26) were recruited as a convenience sample from child and adult subject pools at a public college in the Mid-Atlantic region of the Northeastern United States. Participants were administered the Peabody Picture Vocabulary Test (PPVT; Dunn & Dunn, 2007) as a standardized test of their vocabulary size and the Test of Nonverbal Intelligence (TONI-3, Brown et al., 1997). The adult group was recruited as part of a larger study and matched with the child group using norm-referenced PPVT and TONI scores (for both tests, μ = 100, σ = 15). For PPVT: children M = 114.3, SD = 12.6; adults M = 113.0, SD = 13.7; $t(40)$ = –0.34, p = .736. For TONI: children M = 111.9, SD = 13.0; adults M = 105.3, SD = 13.6; $t(40)$ = –1.59, p = .120. All participants reported native proficiency in English; 4 children and 6 adults reported speaking another language at home. The study was approved by the university IRB. Children received gift cards for their participation; adults received research participation credits.

Repeated Word Association Task

Participants completed a repeated word association task adapted from Sheng & McGregor (2010) and administered on an Acer laptop with external speakers. Participants heard a list of 48 cue words repeated three times, and were instructed to say the first word that came to mind after each cue, for a total of 144 trials. Participants were asked to give a different response to each cue on the list repetitions. Cues varied in their dominant part of speech, comprising 24 nouns (e.g., *bridge, desk*) and 24 verbs (e.g., *drive, swim*). Participants had minimal difficulty completing the task. In total, children produced 57 invalid/null responses (1.9%) and adults produced 6 invalid/null responses (0.2%).

Table 1. List of word characteristic metrics

Metric: Description
Word Embedding Similarity: Cosine similarity between cue and response word embeddings from the BERT language model. Model retrieved from Reimers & Gurevynch (2018)
Taxonomic Similarity: Path similarity between synsets that maximizes the similarity score between cue and response in WordNet. Retrieved from Fellbaum (1998).
Phonological Similarity: Inverse of number of IPA character additions, substitutions, and deletions between cue and response, using the Carnegie Mellon University Pronouncing Dictionary (n.d.)
Concreteness: Average rating of participants asked to rate the concreteness/abstractness of words on a scale from 1 to 5. Retrieved from Brysbaert et al. (2014).
Age of Acquisition: Average estimated age at which a word is known. Retrieved from Kuperman et al. (2012).
Word Frequency (log): Log frequency of lemmas in a corpus of English movie subtitles. Retrieved from Lison & Tiedemann (2016)

Robust Metrics for Lexical Features

Table 1 provides a list of the robust metrics we used to code word association responses. We distinguished two types of features: cue–response similarity and word level features of responses. For cue–response similarity, we coded for word embedding, taxonomic, and phonological similarity, We coded for word embedding similarity of cue and response using the cosine similarity of embeddings vectors retrieved from a large language model with a BERT architecture (Devlin et al., 2019), retrieved from the sentence transformer Python library (Reimers & Gurevynch, 2018). We coded for taxonomic similarity of cue and response using path similarity from WordNet, a dictionary of ontological relations (Fellbaum, 1998). We coded for phonological similarity using the edit distance between the IPA transcriptions for the cue and response using the Carnegie Mellon University Pronouncing Dictionary (n.d.).

For word-level features, we used response concreteness, age of acquisition, and word frequency (log-transformed). We retrieved concreteness and age-of-acquisition statistics from two mega-studies (Brysbaert et al., 2014; Kuperman et al., 2012). We calculated word frequency using log-transformed lemma counts from a corpus of English subtitles (Lison & Tiedemann, 2016).

Results

All analyses were conducted in R. The de-identified datafile with the list of cue words and responses, analysis code, and statistical models are publicly available in an Open Science Foundation repository (Gravelle & Brooks, 2026).

Mixed-effects Models of Response Characteristics

Mixed-effects models were fitted in R using the *lme4* and *lmertest* packages (Bates et al., 2015; Kuznetsova et al., 2017). We ran six models using the response characteristics as dependent variables. We include fixed effects of group (adult = 1) and list repetition (1–3), with an interaction between group and repetition. We nested word characteristics within participants and cues.

Figure 1 presents means and standard deviations for each word characteristic across age groups and list repetitions; for full reporting, see Supplemental Table S1. Starting with the cue–response similarity metrics: For word embedding similarity, there were significant effects of group ($\beta = 0.24$, $SE = 0.01$, $p = .014$) and repetition ($\beta = -0.17$, $SE = 0.00$, $p < .001$), with no significant interaction ($\beta = -0.02$, $SE = 0.00$, $p = .429$). Adults produced responses that were more similar to the cues in their word embedding similarity than children's responses. Across groups, word embedding similarity decreased over list repetitions, with first responses more similar to the cues than later responses. For taxonomic similarity, there were significant effects of group ($\beta = 0.14$, $SE = 0.02$, $p = .003$) and repetition ($\beta = -0.06$, $SE = 0.00$, $p < .001$), and a significant interaction ($\beta = -0.05$, $SE = 0.01$, $p = .045$). Adult responses had higher taxonomic similarity to the cues than child responses, but also showed a steeper decrease in similarity from the first to second list repetition. For phonological similarity, there were significant effects of group ($\beta = -0.08$, $SE = 0.14$, $p = .022$) and repetition ($\beta = -0.12$, $SE = 0.04$, $p < .001$), with no interaction ($\beta = 0.04$, $SE = 0.05$, $p = .069$). Child responses had higher phonologically similar to the cues than adult responses; phonological similarity decreased over list repetitions.

Next, we examined word-level characteristics of responses: concreteness, age of acquisition, word frequency (log transformed). For concreteness, there were significant effects of group ($\beta = 0.17$, $SE = 0.08$, $p = .002$), repetition ($\beta = -0.04$, $SE = 0.02$, $p = .014$), and a significant interaction ($\beta = -0.05$, $SE = 0.02$, $p = .033$). Across time points, adults tended to produce more concrete words as responses than children, with the group difference decreasing over list repetitions. This group difference may reflect the greater reliance on meaning as opposed to sound-based associations in the adult group, which led them to produce responses with higher ratings of concreteness. For age of acquisition, there was a significant effect of repetition ($\beta = 0.07$, $SE = 0.04$, $p < .001$), and a significant group × repetition interaction ($\beta = 0.06$, $SE = 0.05$, $p = .027$), but no significant main effect of group ($\beta = 0.06$, $SE = 0.14$, $p = .373$). Over list repetitions, participants tended to generate words with a later age-of-acquisition, with a larger increase in age-of-acquisition for the adult group.

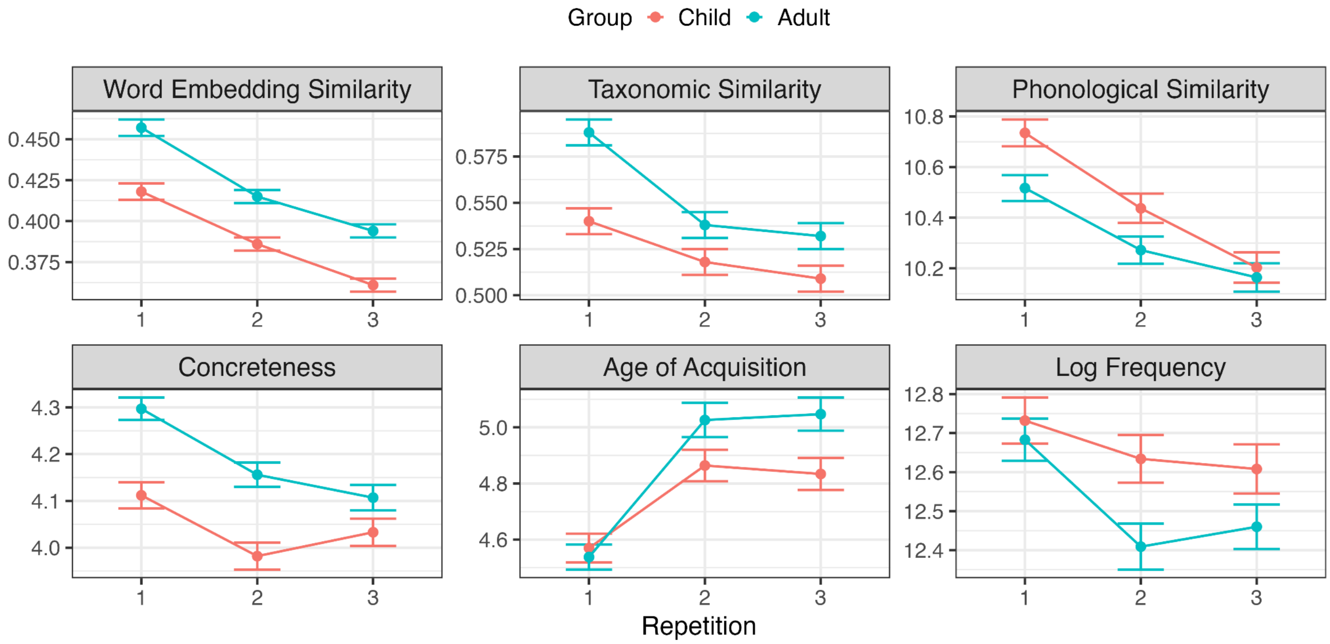

Figure 1. Means and SDs for different response characteristics across repetitions for children and adults ($N = 21$ per group).

For word frequency, there were no significant effects: group (β = –0.08, *SE* = –0.06, *p* = .792), repetition (β = –0.03, *SE* - 0.04, *p* = .112) group × repetition interaction (β = –0.02, *SE* = 0.06, *p* = .376).

Bipartite Latent Space Models

To implement latent space network modeling in a Bayesian framework, we used the PYMC4 library with the nutpie sampler (Abril-Pla et al., 2023). The basic form of the model predicts the presence and strength of an edge between two nodes using a generalized linear regression model. To model endogenous features of a network, the pairwise distances between nodes within a latent space are estimated (Hoff et al., 2002). Friel et al. (2016) extended the latent space network model to account for bipartite networks consisting of two types of nodes, such as the cues and responses in the repeated word association task. The bipartite model estimates the latent positions of words based on the number of times a given response is made to a specific cue, while simultaneously estimating influences of exogenous (word-level, pairwise) and endogenous (network-level) variables.

The first step involved creating rectangular cue × response matrices for each participant group, where entries corresponded to the number of times a specific cue elicited a specific response. In order to distinguish cues and responses in the latent space, we excluded trials where the participant produced one of cues as a response to a different cue (children = 6.4%, adults = 5.3% of trials). The second step involved creating covariate matrices using statistics derived from the robust metrics used in the mixed-effects models; see Table 1. All covariates were standardized to facilitate comparison. Correlation matrices between covariates for both groups are presented in Supplemental Tables S2 and S3. The third step involved building the latent space model, which estimated the pairwise distances between words in a latent space. In order to allow for group-level comparisons of endogenous network characteristics (e.g., clustering), each network was allowed its own latent subspace, linked to a common scaling factor. We then incorporated the pairwise distances into the generalized linear model, using the exogenous variables to predict the edge weights. For the full model equation, see Supplemental Materials.

The bipartite model included fixed effects of the covariates while accounting for the positions of words (cues and responses) in the latent space. The covariate effects can be interpreted as the overall influence of the covariates (e.g, taxonomic similarity between cue and response) on the edge weights between cues and responses. We included a fixed effect for network to control for differences in the strength of word associations and overall network size for the two groups (e.g., due to excluded trials). We also included group-level interactions for each predictor to determine whether the influence of specific covariates differed by group, using the child network as the reference group. We fitted the bipartite model using a negative binomial link function to handle over-dispersion (Gardner et al., 1995), and used a 2-dimensional latent space for ease of visualization.

Table 2 provides a summary of the regression coefficients for the bipartite latent space network model. Note here that the Bayesian framework does not provide *p*-values for effects. Instead, it provides a 95% credible interval (CrI) for each regression coefficient. In describing the model results, we focus on the main effects and interactions with CrIs that did not include 0 (null effect).

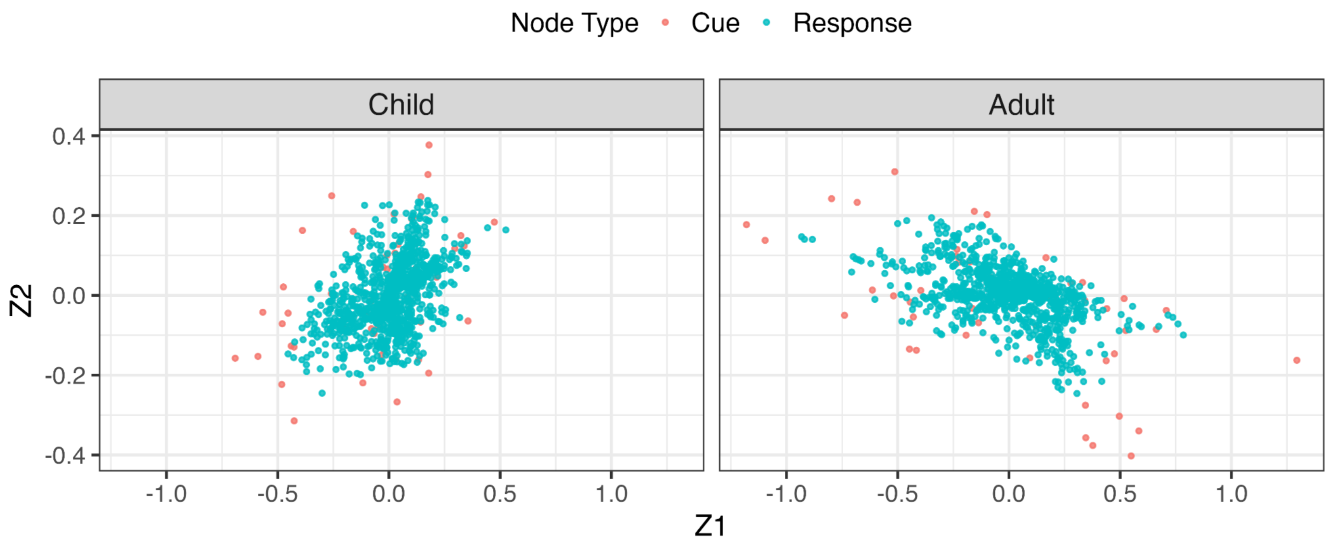

Figure 2. Latent spaces for child and adult word association networks; note that the red dots indicate the cue words.

Table 2. Standardized regression coefficients for the bipartite latent space network model.

Variable	*β*	*SD*	95% *CrI*
Intercept	–3.15	0.22	–3.57; –2.72
Group (child = 0, adult = 1)	0.68	0.32	0.04; 1.31
Word Embedding Similarity	0.95	0.03	0.90; 1.00
Taxonomic Similarity	–0.03	0.03	–0.09; 0.03
Phonological Similarity	0.12	0.04	0.05; 0.19
Concreteness	–0.13	0.04	–0.20; –0.06
Age of Acquisition	–0.20	0.04	–0.28; –0.12
Frequency	0.09	0.04	0.01; 0.17
Group × Word Embedding	0.23	0.04	0.14; 0.31
Group × Taxonomic	0.07	0.05	–0.02; 0.15
Group × Phonology	–0.13	0.05	–0.23; –0.02
Group × Concreteness	0.05	0.05	–0.05; 0.15
Group × Age of Acquisition	0.04	0.07	–0.09; 0.17
Group × Frequency	0.04	0.06	–0.08; 0.16

We start by drawing attention to the large negative intercept. This coefficient reflects the low probability of strong associations among the full set of cues and responses and captures the sparseness of the networks (i.e., most cue–response pairs were not present in the dataset). That said, adults tended to produce stronger word associations than children, i.e., the edge weights between cues and responses tended to be heavier in the adult network.

With respect to relational features (i.e., cue–response similarity), word embedding similarity was the strongest predictor of word associations followed by phonological similarity. With respect to word-level features, we observed influences of age of acquisition, concreteness and frequency on word associations, in decreasing magnitude Here, edge weights tended to be higher for words with earlier age of acquisition, lower concreteness, and higher frequency.

Next we examine the interactions between predictors and groups. Word embedding similarity between cues and responses appeared to have a stronger influence on edge weights in the adult network than in the child network. Conversely, phonological similarity had a somewhat larger influence on edge weights in the child network. Other predictors seemed to yield similar effects across groups. As part of the model fitting process, separate latent spaces were constructed for the child and adult networks. The mean latent positions of cues and responses are shown in Figure 2. The latent space constructed from adult responses was larger and more diffuse than the one for child responses as indicated by the mean distance between nodes (adult pairwise distance: M = 0.29, SD = 0.22; child pairwise distances: M = 0.22, SD = 0.13). A permutation test using 5000 permutations suggests that this group difference was unlikely to occur by chance ($p < .001$).

Next, to compare the local structure (i.e., clustering) within each latent space, we applied Hierarchical Density-Based Spectral Clustering of Applications with Noise (HDBSCAN; Campello et al., 2013), using a minimum cluster size of 2, with all other parameters left at their default value. The adult latent space had a larger number of distinct word clusters (N = 277), than the child latent space (N = 264). A permutation test using 5000 permutations suggests that this group difference was unlikely to occur by chance (p = .018). However, we interpret the observed group difference in word clusters with caution given the slightly higher rates of missing data in the child dataset compared to the adult dataset.

Discussion

The present study used data from a repeated word association task to study the development of the mental lexicon. Using covariates derived from robust metrics (e.g., BERT, WordNet), we examined influences of both relational (cue–response) similarities and word-level features on network structure with emphasis on potential group differences between school-age children and adults. We applied a traditional mixed-effect model to examine how the quality of responses changed over multiple list repetitions, as participants searched long-term memory representations for additional word associations. We then applied bipartite latent space network modeling to estimate how the full set of relational and word-level features influenced network structure in each participant group while controlling for endogenous features of the networks. We introduce the latent space models as a useful tool for exploring influences of exogenous features and pair-wise word similarities on lexical network structure, using the mixed-effects models to provide validation of our key findings.

In general, cue–response similarity tended to decrease over list repetitions in both groups, indicating that later word associations tended to be more dissimilar to the cues in word embeddings and in taxonomic and phonological features. Adults tended to rely more than children on word embedding and taxonomic similarities in generating responses to cues. Whereas prior literature has emphasized age-related increases in the salience of paradigmatic category-based associations (Entwisle et al., 1964; Nelson, 1977), we found an increase in syntagmatic associations as indicated by word embedding similarity of cues and responses (e.g., *swim* eliciting responses like *water, pool,* and *splash*). Participants' reliance on syntagmatic word associations fits with work emphasizing statistical learning in lexical development (Savic et al., 2023; Yu, 2008). It is important to mention that BERT is trained on adult corpora (Devlin et al., 2019), and may better capture the semantic relatedness of word associations of adults as compared to children. Hence, future work should also include child-centric similarity measures (Borovsky et al., 2024).

In contrast to semantic similarity, children tended to rely more than adults on phonological similarity in generating responses to cues (e.g., *swim* eliciting *swing* as a response). This aligns with other work suggesting that phonological similarities between words have greater salience in early childhood (Cronin, 2002; Dewhurst & Robinson, 2004; Sheng & McGregor, 2010). Though previous studies have tended to compare task performance of older vs. younger children, we observed the same shift from school age to early adulthood. The increased salience of phonological similarities in children's word associations might reflect the emphasis on phonological awareness in literacy instruction in early to mid childhood (Anthony & Francis, 2005).

Complementing the mixed-effects models, the bipartite latent space model also indicated increased reliance on word embedding similarities and decreased reliance on phonological similarities in the adult lexical network as compared to the child network. Here, we found word embedding similarity of responses to cues to have the strongest influence on word associations (i.e., weights of connections between nodes in the latent space). This pattern is in keeping with distributional approaches to lexical organization, such as Latent Semantic Analysis (LSA; Landauer & Dumais, 1997) and the Hyperspace Analogue to Language (HAL; Lund & Burgess, 1996), and other more recent vector-based approaches to language organization (e.g., large language models; Bengio et al., 2003; Li & Wang, 2025). The negligible effect of taxonomic similarity on network structure, after controlling for word embedding similarity, is unsurprising, as word embeddings already capture category-based information (Günther et al., 2019). Alternatively, WordNet may be an inherently noisy measure of semantic relatedness (Gao et al., 2015).

In contrast to the relational features (cue–response similarity), we found minimal group differences in reliance on word-level features. In the mixed-effects model, both concreteness and age of acquisition varied across list repetitions, with later responses tending to have lower concreteness and higher age of acquisition. However, in the bipartite latent space model, concreteness was negatively related to edge weights; that is, abstract words tended to have stronger cue-specific associations (e.g., *secret* in response to the cue *whisper*) than concrete words. This pattern runs counter to Ding et al. (2017) who reported that concrete words occupied more central locations within the lexical network on account of their being easier to learn. Further work is required to reconcile these differing results as well as our unexpected finding that the adults' word associations tended to be more concrete than children's. One possibility is that adults, in general, may be more likely to respond to cues with words that are more similar in lexical features such as concreteness or imageability.

More intuitively, responses with lower age of acquisition tended to have higher edge weights suggesting that they featured more prominently in word associations. This aligns with preferential attachment models of lexical development (Cox et al., 2025; Hills et al., 2009; Sailor, 2013), in which newly acquired words tend to form strong associations with words that are already well established in the network.

In comparing the latent spaces derived from children and adult word association networks, we found a more diffuse space for the adults. We also identified more local clustering in the adult latent space, suggesting greater differentiation of their word associations. This pattern matches previous network models indicating more distinct clustering in adults with above-average vs. below-average vocabulary knowledge (Gravelle & Brooks, 2025) and children with typical language development as compared to age-matched peers with developmental language disorder (Brooks et al., 2017). That said, there remain challenges in comparing across networks that should be addressed in future studies. Specifically, under a preferential attachment growth model, one might expect to see a decrease in shortest path length and clustering as the network increases in size, even if the edges are generated at random (Barabási & Albert, 1999). This complicates cross-sectional and longitudinal network analyses, as it is difficult to differentiate network features that are reflective of underlying lexical organization as opposed to artifacts of differences in network size.

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