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Structure and process-level lexical interactions in memory search: A case study of individuals with cochlear implants and normal hearing

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Abstract

Searching through memory is mediated by complex interactions between the underlying mental lexicon and the processes that operate on this lexicon. However, these interactions are difficult to study due to the effortless manner in which neurotypical individuals perform cognitive tasks. In this work, we examine these interactions within a sample of prelingually deaf individuals with cochlear implants and normal hearing individuals who were administered the verbal fluency task for the "animals" category. Specifically, we tested how different candidates for underlying mental lexicons and processes account for search behavior within the verbal fluency task across the two groups. The models learned semantic representations from different combinations of textual (word2vec) and speech-based (speech2vec) information. The representations were then combined with process models of memory search based on optimal foraging theory that incorporate different lexical sources for transitions within and between clusters of items produced in the fluency task. Our findings show that semantic, word frequency, and phonological information jointly influence search behavior and highlight the delicate balance of different lexical sources that produces successful search outcomes.

Keywords: memory search; verbal fluency; computational modeling; word embeddings; language models[1]

Introduction

When individuals search their mental lexicon for items, they are bringing online several processes and knowledge structures. For example, if asked to produce as many *animals* as possible within a fixed duration, i.e., the verbal fluency task (VFT; Bousfield & Sedgewick, 1944), individuals first have to focus on a specific subset of their knowledge (i.e., *animals*). They also have to ignore other words that may be related or come to mind (e.g., where animals live, sounds animal make, characteristics of animals, etc.), but are not relevant to the task at hand. Then, they need to employ some type of search strategy to navigate this subspace of *animals*, which may involve attending to different lexical sources or characteristics to organize the search in a meaningful and efficient manner. Taken together, mental search is a result of interactions between *structure*-level representations and *processes* that operate on those representations.

Several researchers have attempted to understand these structure-process interactions that occur during memory search from a computational perspective. This work has revealed that individuals tend to strategically retrieve items in "clusters" until they have exhausted the local neighborhood, at which point they "switch" to a new cluster, consistent with mechanisms of external search that rely on optimal foraging (Hills et al., 2012; Hills, Todd, & Jones, 2015; Zemla et al., 2023). However, in much of this work, the underlying semantic representations that contribute to the critical question of how clusters and switches are defined are either based on pre-existing norms (Troyer, 2000; Zemla et al., 2020) or derived from distributional semantic models (DSMs) that emphasize meaning-based relationships between words in a high-dimensional space (Hills et al., 2012). However, semantic information is part of an integrated mental lexicon, that also contains other lexical sources of information. Indeed, acquiring a word and its meaning likely involves complex interactions between semantics, phonology, orthography, and acoustic and speech-related information. Although the relationship between meaning and wordform (i.e., phonology/orthography) is typically thought to be arbitrary, there is some recent evidence to suggest that these cues may actually be correlated in natural language (Dautriche et al., 2017), largely due to the functional pressures that are associated with novel language acquisition, as well as semantically related words sharing common etiology (e.g., *conform*, *formulate*, *reform*). Additionally, speech patterns may be particularly critical in forming early mappings between form and meaning (Saffran et al., 1996; Hay et al., 2011). Overall, it is important to investigate how representations that are derived from *multiple* lexical sources contribute to meaning formation, and how this knowledge is used in downstream tasks such as memory search. In particular, comparisons between models of word representation that combine more than one lexical source may be particularly useful in delineating the contribution of lexical sources to semantic organization.

From a process-level perspective, several accounts have emphasized that different types of lexical information may be important when individuals are making transitions within versus between clusters (Hills et al., 2012; Hills, Todd, Lazer, et al., 2015). Specifically, while semantic information may be particularly critical for local within-cluster transitions (e.g., producing *cat-dog*, both within the subcategory of *pets*), other lexical sources such as word frequency may be more useful in transitioning to new clusters (e.g., producing *dog-wolf*, transitioning from *pets* to *canines*). However, task-discrepant clustering has commonly been observed in VFT (Abwender et al.,

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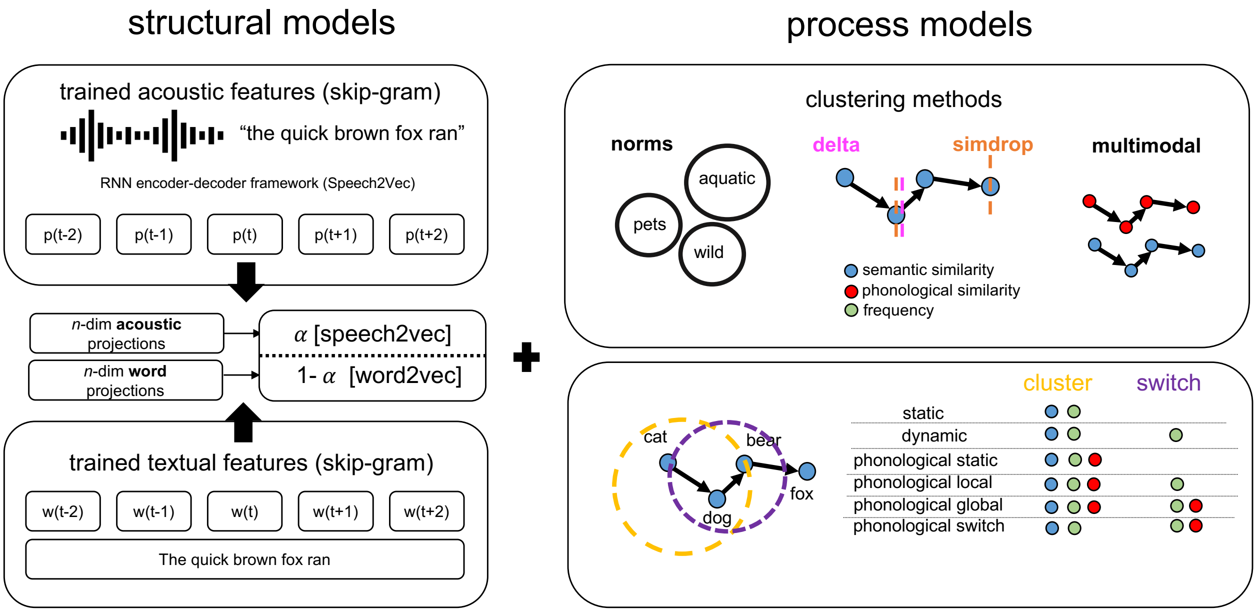

Figure 1: Modeling overview. Representations derived from two different language models trained on textual (*word2vec*) and acoustic (*speech2vec*) features were concatenated to produce multimodal vector representations for all words. These representations were then used in conjunction with process-level models of search that incorporated different clustering and switching methods as well as lexical sources to obtain likelihoods.

2001). Recently, Kumar et al. (2022) provided some preliminary evidence that phonological similarity may be important in mediating local within-cluster transitions. For example, consider the transition from *mouse* to *mole*. Both animals are within the *rodents* subcategory (Zemla et al., 2020), and would therefore be considered semantically similar. However, these two animals are also phonologically similar to each other, given that they share several syllables. Therefore, the transition from *mouse* to *mole* may be mediated by *both* semantic and phonological overlap. Indeed, Kumar et al. (2022) showed that when individuals were asked to group items they had produced during the fluency task in a manner similar to how they may have performed the search, they grouped semantically *and* phonologically similar items together. Additionally, foraging models that incorporated phonology during within-cluster transitions provided the best account of the data. However, the representations used in this work were all derived from text-based models that emphasize semantic information, and it was therefore unclear whether phonology was important at the representational or process level during search. Specifically, is it the case that the representations for *mouse* and *mole* are inherently similar due to sharing semantic *and* phonological features, or is it the case that individuals strategically access this phonological information at the time of search to increase their efficiency?

To isolate the contribution of underlying representations (*structures*) from *processes* that act upon these representations in the fairest way possible, we need a dataset where one of these variables can be "turned off" in principle. For example, to understand how speech and phonology impact the development of meaning-based representations, we would want a sample that does not have access to this information during early word learning. Although this manipulation is impossible to achieve in principle, many deaf children do indeed grow up in an environment with virtually no acoustic input, and experience difficulties achieving conventional language development milestones associated with vocabulary development and semantic organization in long-term memory (Coppens et al., 2013; Ormel et al., 2010). Even among deaf children who receive cochlear implants (CIs), language and other cognitive delays persist (Niparko et al., 2010; Bouchard et al., 2009). Whether these deficits arise due to compromised language *processing* or are simply a result of impoverished *representations* remains unclear. Again, consider the *mouse-mole* example. Would an individual who grew up deaf learn to associate *mouse* and *mole* differently than a normal hearing peer, because they did not have access to the phonological overlap between the two items? If so, is the underlying semantic *representation* different, or is it the strategic *use* of phonology that may be different during memory search?

On one hand, it is possible that there are differences in how CIs organize the lexicon and these differences manifest in the nature of responses provided by CIs in language tasks. If semantic and phonological information are indeed correlated in natural language, one would expect that individuals who lack early phonological input have acquire semantic information differently. This may in turn influence their overall semantic organization and downstream retrieval processes. Kenett et

Table 1: Demographic characteristics for cochlear implant (CIs) and normal hearing (NHs) participants in our sample.

Variable	**Mean (Range) in CIs**	**Mean (Range) in NHs**
Chronological age (years)	15.74 (9.86-26.66)	16.18 (10.2-27.07)
Age at implantation (months)	37.94 (11.07-75.76)	-
Duration of CI use (years)	12.58 (7.79-21.19)	-
Age of onset of deafness (months)	2.41 (0-24)	-
Standardized PPVT-5 [a]	84.69 (42-123)	108.63 (79-132)

[a] *Note*: PPVT-5 stands for the Peabody Picture Vocabulary Test, a standardized test that measures receptive vocabulary knowledge

al. (2013) examined fluency responses from a cohort of CIs using network analysis, and showed that responses from CIs were significantly more clustered and less well-integrated, compared to healthy controls, suggesting critical differences in semantic memory organization. However, Kenett et al. (2013) did not explore a computational model of memory search, so several interpretations are possible. One possibility is that the semantic representations among CIs are relatively comparable to neurotypical individuals, but the *processes* that enable retrieval of these representations are impaired. As such, Ormel et al. (2010) compared deaf and hearing children in their ability to perform the word–picture verification and found that hearing children automatically activated phonology during the task, regardless of whether it was relevant or not, whereas deaf children failed to do so in either case. Whether this tendency to not activate phonology in tasks where it may or may not be relevant extends to CIs is unknown. It is possible that access to speech later in life due to having cochlear implants may make phonology more salient for these individuals. In this case, they may be *more* sensitive to it in language tasks. Alternatively, it may be the case that the lack of early phonological input may make this cue less salient during language processing. Overall, a deeper investigation of how search may differ across CIs and normal hearing individuals can yield novel insights about how these lexical sources interact during memory search. Within this context, atypical populations lacking early phonological input afford a unique opportunity to examine how semantic and phonological jointly influence retrieval as well as the conditions under which attending or not attending to these sources may lead to poorer retrieval performance.

In this work, we explored these questions within a sample of prelingually deaf individuals with cochlear implants (CIs) and neurotypical controls (NHs) who completed the VFT. As discussed, individuals likely learn semantic representations of concepts from multiple sources of information, including but not limited to textual co-occurrence, speech, phonetics, etc. (Kumar, 2021). Therefore, we hypothesized that when individuals are searching through memory, they are likely accessing a "multimodal" semantic representation for different concepts. However, majority of the work in memory search assumes a "unimodal" semantic representation, typically learned from large language corpora (for a review, see Kumar, 2021). To examine how multimodal semantic representations may be used during memory search, we used language models that were pre-trained on text vs. speech to implement a series of *structural* models of semantic organization using varying degrees of text and speech-related information. We were interested in whether a semantic representation model that was *jointly* exposed to meaning and sound-related information provided a better account of search behavior, and if so, whether there were differences in the relative contribution of text-based vs. acoustic-based representations on search outcomes among CIs ans NHs. While such multimodal language models have previously only been used in simple tasks of image classification and semantic similarity (Kiela & Bottou, 2014), there is growing evidence that multimodal representations contain psychological content and do explain behavior across cognitive tasks (De Deyne et al., 2021). Our work presents another instance where multimodal semantic models capture meaningful information about concepts that is useful during memory search.

After creating these multimodal semantic representations, we combined these representations with different process-level models of clustering and switching behavior in the VFT based on optimal foraging theory. Search models based on optimal foraging theory typically differentiate between transitions within and between clusters. We explored a range of these models as well as different clustering and switching methods, to ultimately find the best combination of representations as well as process-level models that accounted for search behavior in our current sample.

Methods

Participants Participants were 30 prelingually deaf, early-implanted (less than 4 years), long-term (over 7 years) child and adolescent users of CIs, and compared with 30 age and nonverbal IQ-matched normal-hearing (NHs) peers. Table 1 displays the demographic characteristics of both samples.

Verbal fluency The Delis-Kaplan Executive Function System (D-KEFS; Delis et al., 2001) subtests were administered to all participants. We only consider the "animals" category, given that this is the most rigorously investigated category in the VFT literature with the most extensive categorization norms. Individuals with cochlear implants (CIs) produced significantly fewer items than individuals with normal hearing (NHs) in the current sample, $F(1,58) = 5.362$, $p = .024$.

Structure-level models We considered two language models as the starting point for creating our hypothesized multimodal lexicons, made available open-source by Chung & Glass (2018). *word2vec* is a standard next-word prediction-based language model that is trained on a large text corpus. *speech2vec* is a variant of *word2vec* that is trained on acoustic information in speech instead of text, where acoustic features are first processed through a recurrent neural network (RNN) encoder-decoder framework, which is subsequently integrated with a skip-gram neural network to predict upcoming acoustic sequences. Following previous work on multimodal DSMs (Kiela & Bottou, 2014), we concatenated the two representations (acoustics-based *speech2vec* and text-based *word2vec*, both trained on the same 500-hour LibriSpeech corpus) into a single vector (weighted by a tuning parameter α), which represented a jointly learned vector for each given word (see Figure 1):

$$v_{\text{word}} = \alpha \times v_{\text{speech2vec}} \parallel (1-\alpha) \times v_{\text{word2vec}}, \tag{1}$$

We explored a wide range of parameter settings for α across four dimensions (50, 100, 200, 300). Additionally, we included two models (“only” *word2vec* and “only” *speech2vec*) as baselines that did not combine these representations, as well as an “average” model that averaged the representations without any tuning parameter. These three models served as baselines for the joint models with the tuning parameter.

Process-level models Our process models were based on prior work by Hills et al. (2012) and Kumar et al. (2022). Specifically, we examined different automated clustering methods in conjunction with process models that differentiated which sources were used within and between clusters.

Four methods of defining clusters and switches were considered: norm-based, similarity drop, multimodal, and delta similarity. The norm-based method assigns switches when items do not share any pre-defined subcategories (e.g., *pets*, *rodents*, *canines*, etc.). The subcategories were obtained from SNAFU (Zemla et al., 2020) and each pairwise transition within an individual’s fluency list was scored as a “cluster” or “switch” based on whether or not two items shared a subcategory (e.g., *cat* and *dog*) or not (e.g., *dog-whale*). The similarity drop method assigns switches based on drops in semantic similarity (e.g., if the semantic similarity significantly drops when going from *cat-dog* to *dog-whale* and rises back again for *whale-shark*, then *dog-whale* is a switch), while the multimodal method assigns switches based on drops in a combined estimate of semantic and phonological similarity (weighted by a tuning parameter). Finally, the delta-similarity method assigns cluster and switch designations based on *relative* rises and drops in similarity, determined by *rise* and *fall* thresholds. Specific details about the switch methods are available in Kumar et al. (2023). For switch methods with thresholds, cluster-switch designations were obtained for a wide range of thresholds and each variant was combined with a process model of memory search.

Three types of process models were considered in conjunction with the clustering methods. While the *static* model computes likelihoods of items produced based on a combination of semantic similarity and word frequency for all transitions (clusters and switches), the *dynamic* foraging model differentiates between clusters and switches and uses global word frequency for between-cluster transitions, and a combination of semantic similarity and word frequency for within-cluster transitions. Similar to Kumar et al. (2022), we also evaluated a suite of foraging models that incorporated phonology in within and between-cluster transitions. Specifically, the *plocal* model uses frequency, semantic, and phonological similarity during within-cluster transitions and frequency during between-cluster transitions. The *pglobal* model uses frequency, semantic, and phonological similarity during within-cluster transitions, and frequency and phonological similarity during between-cluster transitions. Finally, the *pswitch* model uses only semantic similarity and frequency during within-cluster transitions and phonological similarity and frequency for between-cluster transitions (see Figure 1).

Obtaining best-fitting models A vocabulary of 463 animal words was constructed, using a combination of words present in the *word2vec* and *speech2vec* base models, animal words from SNAFU (Zemla et al., 2020) and words produced by participants in our sample. Suitable replacements were made for 50 words produced by participants that were not present in the base models and repetitions were excluded prior to any analyses. We adapted *forager* (Kumar et al., 2023) to compute model likelihoods for different participants, using a combination of different structural and process-level models and obtaining the likelihood of the participant data under each model variant. These likelihoods were then aggregated across items and participants to find the best-fitting model across the two groups. Additionally, for each cue used by the process models (semantic similarity, frequency, and phonological similarity), a β parameter was fit at the participant level, that indicated the “salience” of that parameter for the individual under a given process model of their search[2].

Results

Normal hearing group First, we examined the extent to which different models were able to account for performance in our normal hearing sample. Figure 2 (top panel) displays the overall patterns across different dimensions and concatenated variants of the *structure*-level models, as well as the different foraging models and switch methods.

Overall, models with lower dimensions (i.e., 50) provided a better fit than models with higher dimensions. This is consistent with the patterns reported by Chung & Glass (2018), who found that the models with lower dimensions were best able to capture word similarity across a variety of benchmark tasks. Next, we found that the concatenated variants were

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[2] All data, scripts, and models examined in this work are available at `https://github.com/thelexiconlab/cochlear-project`

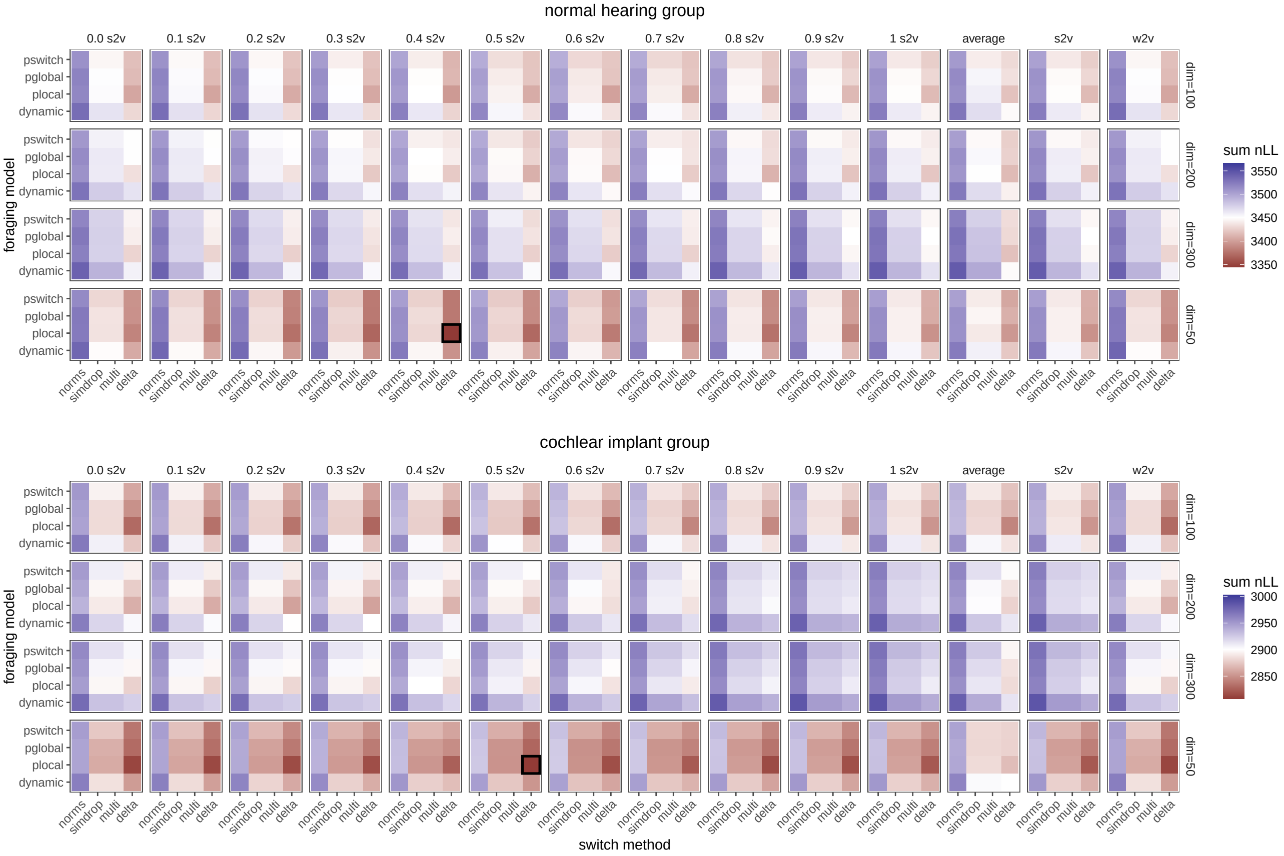

Figure 2: Negative log-likelihoods for models fit to verbal fluency data from the normal hearing and cochlear implant groups. Lower values indicate better fits. Squares outlined in black represent the best-fitting model in each group.

able to perform better than the single-model or the "average" model, and the model that performed best overall assigned slightly lesser weight on embeddings derived from *speech2vec* than *word2vec* ($\alpha = 0.4$, see Equation 1).

The best-performing process model was the dynamic foraging model that incorporated semantic similarity, phonological similarity, and frequency in local transitions and frequency in global transitions (i.e., the *plocal* model in Figure 2), and used the delta similarity method to assign cluster-switch designations, replicating Kumar et al. (2022) and Lundin et al. (2023). This suggests that individuals with normal hearing treat local transitions within clusters differently than transitions between clusters. While within-cluster transitions emphasize *all* types of lexical sources, between-cluster transitions tend to emphasize word frequency.

Cochlear implant group Within our cochlear implant sample, as shown in Figure 2 (bottom panel), we found that the *structure*-level model that best fit the data equally emphasized the *speech2vec* representations and *word2vec* representations ($\alpha = 0.5$, see Equation 1), suggesting that CIs may be equally emphasizing the textual and speech-related features in their lexicon. At the process level, we found that the best-performing model for CIs was the same as their NH peers,

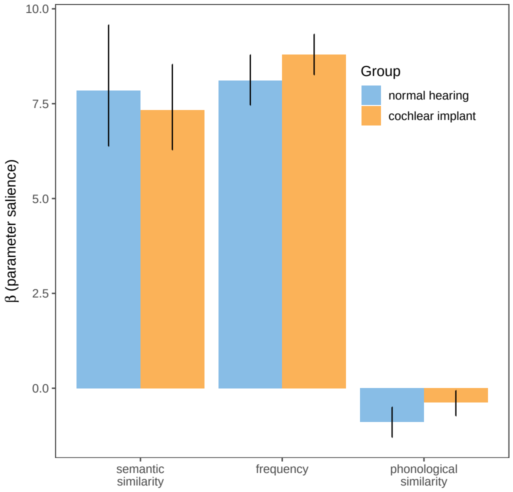

Figure 3: Parameter salience for lexical sources from the best-fitting models at the individual level. Individuals with cochlear implants showed marginally more reliance on frequency and phonological similarity. Error bars represent bootstrapped 95% confidence intervals.

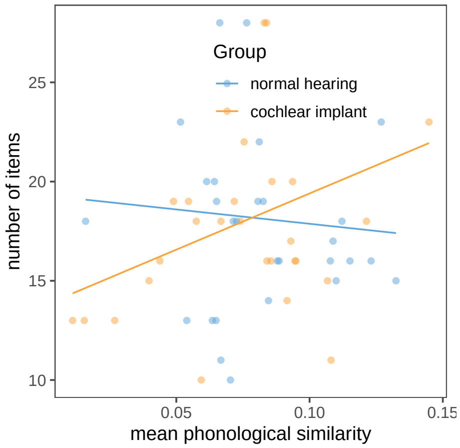

Figure 4: Total number of items produced as a function of mean consecutive phonological similarity, based on length-matched lists across both groups.

i.e., the dynamic foraging model that incorporated all lexical sources in local transitions and frequency in global transitions (i.e., the *plocal* model).

Lexical sources We next investigated the relative usage of the three sources (word frequency, semantic similarity, and phonological similarity) across groups, by examining the best-fitting salience (β) parameters for each individual. As shown in Figure 3, CIs used phonological similarity (b= .51, t = 1.87, p = .07) and word frequency (b= .69, t = 1.60, p = .114) marginally more than NHs, while there were no differences in their use of semantic similarity (p = .62).

Fluency performance The finding that CIs were emphasizing phonology more than their NH peers was surprising, as one might expect that the lack of exposure to sounds early in life may have had the opposite effect. One possibility is that these patterns may be confounded with the total number of items produced, i.e., since CIs produce fewer items overall, it is possible that phonologically similar items occur earlier in the lists and NHs continue to produce more dissimilar items over time, whereas CIs do not produce those remote items at all. To address this possibilty, we re-ran all analyses by truncating the participant lists to the minimum number of items produced by either pair. The overall patterns were robust to list length, such that the best-fitting models for CIs were still ones that emphasized phonology more than NHs. Additionally, we examined whether the total number of items produced was related to the average consecutive phonological similarity across the two groups. As shown in Figure 4, producing more phonologically related items was related to producing more items overall among CIs, confirmed by a significant interaction, $F(1,112)$= 7.74; p = .006, and this pattern did not reliably vary by whether the analysis was conducted on truncated or complete lists (p = .60).

Discussion

In this work, we explored how different lexical sources at the *structural* and *process* level jointly influence search behavior within the verbal fluency task. While semantic and phonological information, in addition to word frequency have been previously implicated within the context of VFT (Abwender et al., 2001; Hills et al., 2012), separating the contribution of different lexical sources at the level of representation and processes has been difficult from a computational perspective. This issue is further compounded by the fact that neurotypical individuals are generally perform well in the VFT and it is therefore difficult to assess which of these correlated sources are critical to successful performance in the task.

To better elucidate the joint influences of different lexical sources on search, we compared fluency lists from a sample of individuals with cochlear implants with individuals with normal hearing. Specifically, we explored how different concatenated variants of text and speech-based language models, when combined with a series of foraging models account for search behavior in the VFT. We found important similarities and differences at both the structure and process level between CIs and NHs. First, both groups were sensitive to representations derived from text and speech, suggesting that the lexicon is represented in a multimodal format across both groups. However, while CIs equally emphasized representations derived from speech and text, NHs de-emphasized the speech-based representations in favor of the text-based representations. This may suggest that among neurotpyical individuals, speech-related cues may be overtaken by textual or linguistic cues over time, whereas CIs tend to rely on these cues a lot more than their peers. In line with this hypothesis, although both groups appeared to use phonology as a cue during search, CIs attended to phonology and word frequency marginally more than their NH peers, and this also improved their overall performance. It is possible that exposure to sound later in life heightens the salience of speech-related cues among CIs, and this cue is used in a compensatory manner during search tasks, when it is difficult to access semantically related information. Overall, these findings suggest that there may be differences in how concepts are organized (as suggested by Kenett et al., 2013) as well as how concepts are then retrieved in response to task constraints between CIs and NH peers.

Future work could further investigate these patterns in a larger sample and across diverse domains, to provide a more comprehensive picture of how different lexical sources are at play during searching through memory. Broadly, our work presents a novel perspective on how lexical sources may contribute to search behavior at *multiple* levels. Our findings highlight how memory search is the result of a complex process of activating relevant semantic and phonological neighbors within the lexicon, and then navigating the lexicon using multiple sources of information.

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