Tracking the time course of phonological neighborhood clustering effects in spoken word recognition

Charles Redmon,[a] Annie Tremblay,[b] and Michael S. Vitevitch[c]

[a]Dept. of Linguistics, Univ. of Kansas, 1541 Lilac Ln., Lawrence, KS, 66045; redmon@ku.edu

[b]Dept. of Linguistics, Univ. of Kansas, 1541 Lilac Ln., Lawrence, KS, 66045; atrembla@ku.edu

[c]Dept. of Psychology, Univ. of Kansas, 1415 Jayhawk Blvd., Lawrence, KS, 66045; mvitevit@ku.edu

Author Note

Correspondence:

Charles Redmon

428 Blake Hall

1541 Lilac Lane

Lawrence, KS, USA 66045

redmon@ku.edu

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Abstract

This study used visual-world eye tracking to examine the effect—first observed in Chan and Vitevitch (2009)—of the phonological neighborhood clustering coefficient on the time course of lexical access in spoken word recognition. Target words from neighborhoods with relatively high clustering (i.e., neighbors of the target word are also neighbors with each other) showed a significant lag in eye fixations relative to words from less clustered neighborhoods after controlling for neighborhood density, target frequency, neighborhood frequency, and multiple phonotactic probability measures. This effect was also influenced by lexical frequency, neighborhood density, and neighborhood frequency, suggesting that neighborhood clustering is not only a relevant factor in spoken word recognition, but it should be a factor accounted for by any viable model of spoken word recognition.

Keywords: eye tracking, word recognition, clustering coefficient, phonological network

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1. Introduction

Many laboratory-based tasks have been used to test hypotheses about the processes involved in spoken word recognition, including phone/word identification (McQueen, Norris, & Cutler, 1994; Norris, Cutler, & McQueen, 2003) and discrimination (Luce & Large, 2010; Vitevitch & Luce, 1999), lexical decision (Buchanan, Westbury, & Burgess, C., 2001; Marslen-Wilson & Warren, 1994; Norris et al., 2003; Vitevitch & Luce, 1999), naming (Buchanan et al., 2001; Vitevitch & Luce, 1998, 1999), priming (Connine, Blasko, & Titone, 1993; Goldinger, Luce, & Pisoni, 1989; Marslen-Wilson & Zwitserlood, 1989), and gating (Grosjean, 1985; Marslen-Wilson & Warren, 1994). Unfortunately, all of these tasks, even those that use reaction time as a dependent variable, provide information about the spoken word recognition process only after the process has been completed. A more recently developed method, eye tracking, provides researchers with insight into the dynamics of lexical access and selection as the acoustic signal unfolds (Allopenna, Magnuson, & Tanenhaus, 1998; Dahan, Magnuson, & Tanenhaus, 2001; Dahan, Magnuson, Tanenhaus, & Hogan, 2001; Huettig, Rommers, & Meyer, 2011). In the present study we used the visual-world eye tracking paradigm to examine the influence—first observed in Chan and Vitevitch (2009)—of the *phonological neighborhood clustering coefficient* on the time course of lexical access in spoken word recognition.

The phonological neighborhood clustering coefficient is a measure derived from network science where the mental lexicon is viewed as a *network* composed of *nodes* that represent words, and *edges* that connect nodes that are related in some way. In the network examined in

Vitevitch (2008), nodes were connected if the words they represented were phonologically related—that is, if they differed by a single phoneme addition, subtraction, or substitution (for lexical networks with nodes connected based on the semantic relationships among words, see Hills, Maouene, Maouene, Sheya, & Smith, 2009; Evens, 2009; Sowa, 2014; and Wulff, De Deyne, Jones & Mata, 2019). Clustering coefficient measures the extent to which the neighbors of a target word also neighbor each other, and is formally defined as the proportion of links in the neighborhood of a word out of the total number of possible links in that neighborhood. Chan and Vitevitch (2009) found that words with high *clustering coefficients* (CC) were recognized more slowly and less accurately than words in less connected neighborhoods, despite being equivalent in neighborhood density/frequency, among other measures. This finding was later replicated in Altieri, Gruenenfelder, and Pisoni (2010) using spectrally degraded stimuli. However, evidence for this effect of neighborhood clustering remains limited to offline tasks.

The present study replicates Chan and Vitevitch (2009) using the visual-world eye tracking paradigm, and provides critical temporal information that will help clarify the relative timing of such effects, particularly as a function of other factors, such as neighborhood density, which has been shown to exhibit complex temporal patterns of early facilitation and late inhibition of target access in neighborhoods of higher density (Magnuson et al., 2007). Based on the results in Chan and Vitevitch (2009), eye fixations to targets in high-clustering (high-CC) neighborhoods are predicted to be delayed relative to those in low-clustering (low-CC) neighborhoods. Furthermore, given that CC represents the amount of phonological relatedness among a set of (minimal) competitors with the target word and that such relatedness should reinforce activation among candidate items (thereby increasing competition with the target), any variables reflecting the size and amount of competitor activation—such as lexical frequency and neighborhood density/frequency—should magnify the effect of clustering coefficient.

2. Methods

2.1. Participants

Forty native English listeners were recruited from the Psychology Department Research Participation Pool at the University of Kansas. Two participants were not analyzed because they were bilingual from birth, bringing the total to 38. None of the listeners reported speech or hearing impairments, and all received course credit as compensation.

2.2. Materials

The 76 target stimuli used in the present study were adopted directly from the stimuli used in Chan and Vitevitch (2009), which were produced in isolation by the third author. Recordings were made in an anechoic chamber at 44.1 kHz, and normalized to 70 dB mean amplitude in Praat 6.0 (Boersma & Weenink, 2016). The critical targets comprised 38 high-CC words ($\bar{x}$ = 0.35, s = 0.01) and 38 low-CC words ($\bar{x}$ = 0.25; s = 0.01). The 76 words were presented in their orthographic form due to constraints on imageability (for discussion of the use of orthographic words in visual-world eye tracking experiments, see McQueen & Viebahn, 2007 and Huettig & McQueen, 2007).

Critical target items were controlled for frequency, familiarity, cohort size (initial mono- and di-phone probability), neighborhood density, and neighborhood frequency. Visual distractors were controlled for phonological overlap with the target and each other (minimum 2 phonemes different, no onset competitors), orthographic overlap (minimum 2 graphemes different), and overall frequency and neighborhood density across conditions. For a complete list of the test items, see the Appendix.

2.3. Procedure

Each participant completed 80 trials. The first four trials served as practice and used words unrelated to the experimental stimuli. Experimental trials were presented in a single block of 76, with periodic interruptions to apply a drift correction when fixations drifted away from the center fixation cross at the beginning of a trial.

Each trial proceeded as follows. A screen with a fixation cross was displayed for 2.5 seconds, at which participants were instructed to stare. Next, participants heard over headphones “Click on” (spoken by the same speaker as for the target words), which lasted 600 ms. Following the “Click on” instruction, a screen displaying the target word and the three distractors appeared. Next, the target word was played over headphones 200 ms following the appearance of the four-word display, meaning participants had 200 ms of preview time. This interval was chosen based on Huettig and McQueen (2007), who studied recognition of printed words as a function of various lexical characteristics, and thus needed to prevent participants from accessing an item in their mental lexicon prior to stimulus onset, a necessary condition for the present study. Upon identifying the target, participants clicked on the word, after which the next trial began.

Eye fixations were recorded throughout the experiment using an EyeLink II (2006) eye tracker, sampled at 250 Hz, with calibration and recording done on the participant’s right eye. The experiment was designed and run in Experiment Builder (2015).

3. Results

Fixation data were analyzed as temporal trajectories of proportions of fixations to the target word over the 1000 ms following the onset of auditory presentation of the target word. Fixations were analyzed in a growth curve model (a longitudinal mixed-effects linear regression), where time was represented as an orthogonal cubic polynomial included in interaction terms with the conditions of interest in the following models: (1) CC (high, low); (2) CC by Target Frequency (high, low); (3) CC by Neighborhood Density (high, low); and (4) CC by Neighborhood Frequency (high, low). For each of the above variables, levels were controlled such that they did not differ significantly on any of the control variables, nor were there significant interactions with CC in predicting any control variable.

Figure 1 displays fixation trajectories for high and low CC conditions (left panel), along with results for a model where CC was treated continuously (right panel). Polynomial fits to those trajectories over the 1,000 ms period following word onset derive from a longitudinal multilevel model with the interaction between CC (high [ref], low) and an orthogonal cubic polynomial representation of time (t, t^2, t^3) as fixed effects, and random intercepts and random slopes for the time terms (t, t^2, t^3) by listener. All models were fit with the lme4 package in R (Bates et al., 2014; R Core Team, 2018).

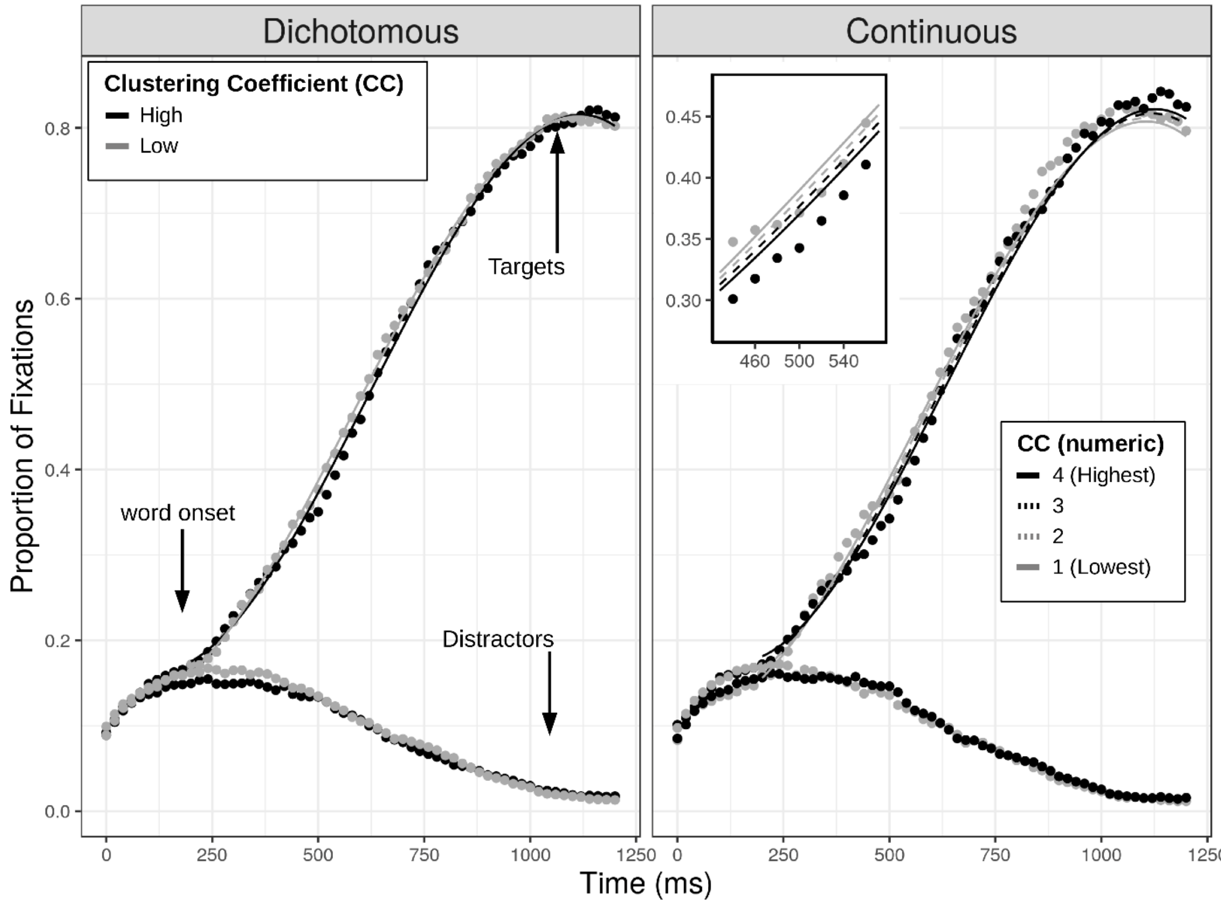

Figure 1. *Mean eye fixation trajectories for targets and distractors (dots), and model-predicted trajectories for target items (lines) in the low (gray) and high (black) clustering coefficient conditions. The left panel shows the dichotomous CC variable (following Chan & Vitevitch, 2009), and the right panel shows results of the continuous CC model. In the latter, only the observations from the lowest (gray dots) and highest (black dots) levels of clustering coefficient are shown, with predictions shown in solid and dashed lines for all four levels (see inset graph for a closer view of the interval between 425 and 575 ms).*

As can be seen in the left panel of Figure 1, there is little separation between the two CC curves. However, crucially, the statistical analyses revealed that the words in low-CC neighborhoods showed significantly greater fixations overall relative to high-CC targets (β = 0.006, t = 7.664, CI = [0.005, 0.008]), as well as significant interactions between CC and t^2 (β = –0.105, t = –8.215, CI = [–0.132, –0.078]) and t^3 (β = 0.041, t = 3.207, CI = [0.018, 0.067]). The significant quadratic interaction comes from the more concave temporal trajectory in the low-CC condition due to slightly faster convergence on the target over the first 500 ms following word onset. Similarly, as all of the fitted polynomials have negative cubic terms, the significant positive interaction between t^3 and CC reflects the fact that low-CC fixation trajectories show a more linear rise to asymptote than do high-CC, which show an initial delay and therefore greater curvature. Thus, we were able to replicate the dichotomous (high vs. low CC) neighborhood clustering effect shown in Chan and Vitevitch (2009), though the size of the slowdown in the high-CC condition was small.

To probe the effect further, we created a new four-level CC variable, which was treated as a continuous variable from 1 (lowest CC) to 4 (highest CC). This semi-continuous representation of CC, where the variable is divided into four levels and treated continuously, was necessary because entering the clustering coefficient directly into the model as a true continuous variable would have required the direct inclusion of control variables in the model, which would have made it overparameterized and inestimable. The 4-level CC variable allows us to control these variables across the four levels, while still testing whether the dichotomous high-CC vs. low-CC pattern is consistent with more granular divisions that pattern monotonically. As before, time was modeled as a cubic polynomial that interacted with CC, and the random effects structure remained the same as in the previous analysis.

The results of the continuous-CC model are shown in the right panel of Figure 1. Importantly, these results show that eye fixations do indeed converge on the target earliest at the lowest CC level, latest at the highest CC level, and intermediately for Levels 2 and 3. As before, clustering coefficient was a significant predictor of both overall target fixations ($\beta = -0.002$, $t = -3.922$, CI = [–0.002, –0.001]) and the rate at which fixations converged on the target, as represented in the interaction between CC and t^2 ($\beta = 0.067$, $t = 10.09$, CI = [0.054, 0.078]).[1] Further interactions were obtained with t ($\beta = 0.023$, $t = 3.432$, CI = [0.054, 0.078]) and t^3 ($\beta = –0.020$, $t = –3.014$, CI = [–0.033, –0.007]), consistent with the general prediction of delayed target recognition in increasingly clustered lexical neighborhoods.

Figure 2 displays the effect of CC as a function of target frequency (top panels), neighborhood density (middle panels), and neighborhood frequency (bottom panels) in Models 2–4, respectively. Beginning with the effect of target frequency, items were split into high and low frequency groups within each level of CC while ensuring the two were not confounded any control variables. Target fixation proportions were modeled as before but with CC (high [ref], low) included in interactions with target frequency (high [ref], low); all other fixed and random effects remained the same.

As Figure 2 illustrates, the detrimental effect of high neighborhood clustering shown in Figure 1 appears to be restricted to words of higher frequency. Model results revealed a significant interaction between clustering coefficient, target frequency, and t^2 ($\beta = 0.094$, $t = 3.425$, CI = [0.036, 0.150]), indicative of a significant change in the difference in concavity (speed of converging on the target) between high-CC and low-CC when comparing high frequency to low frequency targets. That is, there was a substantial difference in coefficients of t^2 in high-CC and low-CC for high frequency items ($\beta = –0.152$, $t = –7.818$, CI = [–0.191, –0.116]) but much less so for low frequency items ($\beta = –0.058$, $t = –2.975$, CI = [–0.099, –0.020]). Further significant interactions were obtained between CC, target frequency, and the intercept (β = –

[1] Parametric bootstrap confidence intervals have been provided instead of *p*-values because the question of proper determination of degrees of freedom for *t*-statistics in mixed-effects models remains a matter of debate. Bootstrap intervals were computed for each parameter for 1000 iterations, and show the median 95% range, which is considered significant if the range does not include zero.

0.029, t = –16.94, CI = [–0.033, –0.026]), t (β = 0.414, t =15.092, CI = [0.360, 0.465]), and t^3 (β = –0.181, t = –6.577, CI = [–0.235, –0.123]).

Next, we examined whether the effect of neighborhood clustering is also influenced by neighborhood density (ND). High-CC and low-CC words were divided into high and low ND groups, which were controlled following the procedures outlined above. Mean trajectories of fixation proportions by clustering coefficient and neighborhood density are shown in the middle panels of Figure 2, illustrating no clear difference in the two conditions for high ND words, while for low ND words the effect of CC is in the same direction as was observed overall (i.e., delayed fixations for high CC words relative to low CC). Results of the CC×ND model showed significantly greater looks to low-CC targets relative to high-CC targets (β = 0.006, t = 4.557, CI = [0.003, 0.008]) for both low and high-ND words (no significant CC×ND interaction overall: CI = [–0.003, 0.004]). However, the trajectories in each condition differed, with low-CC stimuli eliciting significantly fewer early fixations to target but an ultimately faster later convergence in denser neighborhoods (CC×t: β = 0.217, t = 10.78, CI = [0.176, 0.257]; CC×t^2: β = –0.139, t = –6.932, CI = [–0.180, –0.100]), whereas in low-ND neighborhoods the relation reverses (CC×ND×t: β = –0.469, t = –16.51, CI = [–0.526, –0.414]; CC×ND×t^2: β = 0.068, t = 2.384, CI = [0.012, 0.120]; CC×ND×t^3: β = 0.114, t = 4.023, CI = [0.064, 0.172]).

Finally, we examined whether the effect of CC similarly depended on the average frequency of words in a target's neighborhood (the neighborhood frequency, NF). As before, high-CC and low-CC groups were subdivided into high and low NF groups, which were controlled for confounding factors as in previous models. Figure 2 (bottom panels) displays the mean fixation trajectories for high-CC and low-CC words in neighborhoods of relatively high and low frequency. Results of the CC×NF model were comparable to the results for target frequency in showing a significant disadvantage for high-CC words, but restricted to neighborhoods of relatively high average frequency. Significant interactions were obtained between CC, NF, and the intercept (β = –0.009, *t* = –5.279, CI = [–0.013, –0.006]), t (β = 0.427, *t* = 15.05, CI = [0.373, 0.480]), and t^3 (β = –0.141, *t* = –4.961, CI = [–0.196, –0.085]). That is, the advantage for low-CC words in high NF contexts was significantly reduced in low NF contexts. This result is consistent with predictions that competition effects should compound under conditions yielding greater activation of competitors, such as when those competitors are of comparatively higher frequency.

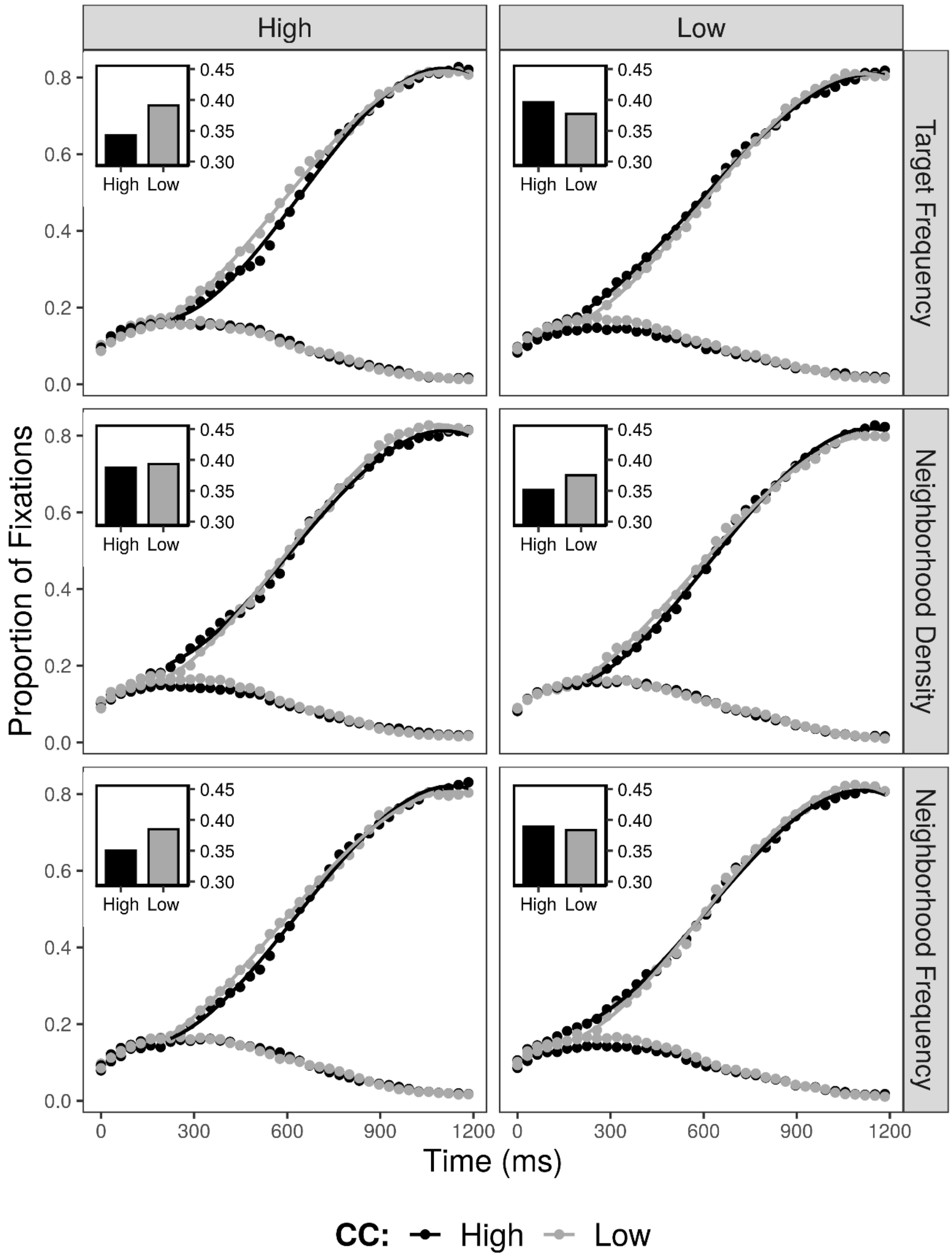

Figure 2. *Mean fixation trajectories (dots) and model predictions (lines) for high-CC (black) vs. low-CC (gray) conditions as a function of Target Frequency (high, low; upper left panel, upper right panel), Neighborhood Density (high, low; middle left, middle right), and Neighborhood Frequency (high, low; lower left, lower right). Mean fixations over the 350 to 650 ms interval post-word-onset* are shown in the inset bar plots.

4. Discussion

The present study provides initial evidence for the online role of phonological neighborhood clustering in spoken word recognition. Although the size of the effect is relatively small, it is comparable to the cohort and neighborhood density effects observed in Magnuson et al. (2007) in the absence of an on-screen competitor. Words from highly clustered neighborhoods, all else equal, showed significant delays in recognition relative to words from neighborhoods exhibiting relatively less clustering. Further, this effect was largely restricted to words of higher frequency and neighborhoods of high frequency, which is consistent with the prediction that competition effects should be compounded by factors such as lexical frequency which enhance the speed and retention of activation of items in the lexicon.

Interactions between clustering coefficient and neighborhood frequency are consistent with these predictions, as highly frequent neighborhoods mean concomitant increases in the likelihood of activating any given word in the neighborhood from the input. From this increase in activation likelihood, we expect increases in uncertainty about the target and therefore delayed fixations relative to low-CC neighborhoods (Vitevitch et al., 2011). Neighborhood density results were less clear, however, and bring to mind the complex patterns reported in Magnuson et al. (2007), where high neighborhood density is initially facilitative and later inhibitory in its fixation trajectory. Here, this pattern (initial facilitation from greater neighborhood connectivity) is shown as a function of clustering coefficient in high ND environments, with the reverse pattern in low ND contexts (i.e., delayed initial access but faster later convergence on the target relative to denser neighborhoods).

Replicating an influence of clustering coefficient on spoken word recognition is important because current models of spoken word recognition assume (implicitly or explicitly) that the lexicon is *unstructured* (*i.e.*, words are encoded with certain phonological or semantic features, but no relations or similarity structures between items are represented). This approach has been described as the ‘bag of words’ view of the lexicon (Harris, 1948), not to be confused with bag-of-words models in natural language processing. Models of this type include Cohort (Marslen-Wilson & Welsh, 1978; Marslen-Wilson, 1987; Gaskell & Marslen-Wilson, 1997), TRACE (McClelland & Elman, 1986), Shortlist (Norris, 1994; Norris & McQueen, 2008), NAM (Luce & Pisoni, 1998), and ARTPHONE (Grossberg, 2003). However, the approach developed in Vitevitch (2008) and Vitevitch, Ercal, and Adagarla (2011) suggests instead that the lexicon is structured by phonological relationships among words, and, importantly, that the process of spoken word recognition is influenced by those relationships. For a model of spoken word recognition to remain viable (see the simulations in Chan & Vitevitch, 2009), it must account for the influence of structured phonological relationships among words on the process of spoken word recognition as observed in the present study.

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Appendix

Target	CC_2	CC_4	TF_2	ND_2	NF_2	CC	TF	ND	NF	PSF	BPF
bead	LC	1	low	high	high	0.225	0.301	26	1.220	0.121	0.004
beat	LC	1	high	high	high	0.237	1.839	33	1.280	0.149	0.005
boot	LC	1	low	high	low	0.240	1.146	32	0.910	0.139	0.004
bush	LC	1	low	low	low	0.133	1.176	6	0.830	0.069	0.002
couch	LC	1	low	low	low	0.194	1.114	9	0.620	0.110	0.002
gas	LC	1	high	low	low	0.251	1.996	19	0.860	0.184	0.010
goat	LC	1	low	high	low	0.240	0.845	26	0.910	0.141	0.006
gull	LC	1	low	high	low	0.229	0.301	21	0.750	0.139	0.006
ledge	LC	1	low	low	low	0.235	0.845	18	0.820	0.118	0.006
lick	LC	1	low	high	high	0.220	0.602	32	1.040	0.184	0.015
lime	LC	1	low	low	low	0.261	1.146	23	0.970	0.118	0.005
lip	LC	1	low	high	low	0.249	1.279	29	0.810	0.167	0.011
lock	LC	1	high	high	low	0.230	1.380	31	0.930	0.148	0.005
loss	LC	1	high	low	high	0.222	1.940	19	1.140	0.129	0.003
miss	LC	1	high	low	low	0.217	2.413	23	0.910	0.232	0.025
mood	LC	1	high	low	low	0.257	1.580	17	1.030	0.117	0.002
pass	LC	1	high	high	high	0.239	1.954	24	0.960	0.243	0.016
sauce	LC	1	low	low	high	0.222	1.322	10	1.250	0.198	0.002
wide	LC	1	high	high	high	0.265	2.100	26	1.060	0.093	0.004
beach	LC	2	high	low	high	0.261	1.833	18	1.040	0.091	0.003
cough	LC	2	low	low	high	0.255	0.903	11	1.100	0.129	0.003
dead	LC	2	high	low	high	0.272	2.243	24	1.250	0.163	0.011
debt	LC	2	low	high	high	0.262	1.146	28	1.360	0.191	0.012
deck	LC	2	low	low	low	0.279	1.380	20	1.000	0.178	0.014
fat	LC	2	high	high	high	0.267	1.785	28	1.370	0.192	0.009
fate	LC	2	high	high	high	0.266	1.568	29	1.470	0.142	0.005
fell	LC	2	high	high	high	0.267	1.968	30	1.290	0.193	0.011
live	LC	2	high	low	low	0.257	2.250	15	0.940	0.154	0.009
log	LC	2	low	low	high	0.282	1.079	13	1.280	0.069	0.002
luck	LC	2	low	high	low	0.249	1.681	26	0.880	0.127	0.004
merge	LC	2	low	low	low	0.236	1.041	11	0.650	0.093	0.002
purse	LC	2	high	high	low	0.240	1.176	19	0.960	0.188	0.007
rhyme	LC	2	low	low	low	0.243	0.699	25	0.940	0.134	0.003
save	LC	2	high	high	high	0.264	1.799	22	1.010	0.155	0.003
word	LC	2	high	high	high	0.269	2.439	19	1.290	0.083	0.003
dog	LC	3	high	low	low	0.286	1.881	8	0.820	0.086	0.002
mile	LC	3	low	high	high	0.275	1.690	28	0.950	0.165	0.005
rise	LC	3	high	low	high	0.276	2.013	21	1.050	0.105	0.003

leap	HC	2	low	high	low	0.331	1.176	30	0.930	0.103	0.004
lull	HC	2	low	low	low	0.314	0.477	15	0.660	0.147	0.006
perk	HC	2	low	low	low	0.307	0.301	22	0.720	0.163	0.006
bug	HC	3	low	high	high	0.308	0.699	26	1.430	0.108	0.005
bull	HC	3	low	low	low	0.321	1.176	13	0.800	0.135	0.003
call	HC	3	high	high	high	0.311	2.276	26	1.430	0.183	0.006
dig	HC	3	low	high	high	0.368	1.041	17	1.190	0.166	0.019
dot	HC	3	low	high	low	0.342	1.146	26	1.060	0.178	0.005
feel	HC	3	high	high	low	0.338	2.336	30	1.060	0.152	0.005
lag	HC	3	low	high	low	0.311	0.602	27	0.730	0.131	0.007
lease	HC	3	low	high	high	0.339	1.041	27	1.020	0.145	0.004
lose	HC	3	high	low	low	0.331	1.771	17	1.000	0.076	0.003
math	HC	3	low	low	high	0.314	0.699	15	1.230	0.144	0.011
pearl	HC	3	low	low	low	0.314	1.000	21	0.980	0.183	0.005
ring	HC	3	high	high	high	0.316	1.699	23	1.040	0.158	0.020
ripe	HC	3	low	low	low	0.316	1.176	20	0.930	0.122	0.003
seal	HC	3	high	high	high	0.338	1.255	31	1.200	0.208	0.006
size	HC	3	high	low	high	0.318	2.143	12	1.290	0.157	0.004
weak	HC	3	high	high	high	0.307	2.489	22	0.930	0.106	0.003
bash	HC	4	low	high	low	0.333	0.000	24	0.820	0.138	0.008
bath	HC	4	high	low	high	0.397	1.431	17	1.260	0.138	0.007
bib	HC	4	low	low	high	0.359	0.477	13	1.250	0.173	0.006
case	HC	4	high	low	high	0.355	2.560	22	1.140	0.201	0.005
dish	HC	4	low	low	high	0.455	1.230	12	1.220	0.156	0.016
dug	HC	4	high	low	low	0.359	1.230	22	0.830	0.109	0.004
foul	HC	4	low	low	high	0.404	0.778	17	1.000	0.130	0.001
full	HC	4	high	low	high	0.457	2.364	15	1.450	0.131	0.003
gain	HC	4	high	high	high	0.367	1.875	25	1.220	0.151	0.004
gang	HC	4	high	low	low	0.400	1.362	15	0.650	0.117	0.007
gum	HC	4	high	high	low	0.425	1.176	16	0.930	0.115	0.007
leaf	HC	4	low	high	low	0.387	1.114	25	0.900	0.086	0.003
leave	HC	4	high	high	low	0.342	2.314	26	0.760	0.089	0.004
look	HC	4	high	low	high	0.419	2.602	17	1.210	0.098	0.001
love	HC	4	high	low	high	0.327	2.367	11	0.910	0.097	0.003
mall	HC	4	low	high	high	0.312	0.602	24	1.270	0.147	0.004
meal	HC	4	high	high	low	0.354	1.491	28	0.920	0.163	0.005
mouse	HC	4	low	low	low	0.352	1.041	14	0.930	0.146	0.002
wire	HC	4	high	high	low	0.355	1.633	22	0.860	0.133	0.004

Table A1. Lexical characteristics of target words: dichotomous clustering coefficient (CC_2, HC vs. LC), four-level CC (CC_4), dichotomous target frequency (TF_2), dichotomous neighborhood density (ND_2), dichotomous neighborhood frequency (NF_2), clustering coefficient (CC), log-transformed target frequency (TF), neighborhood density (ND), log-transformed mean neighborhood frequency (NF), positional segment frequency (PSF), and biphone frequency (BPF).