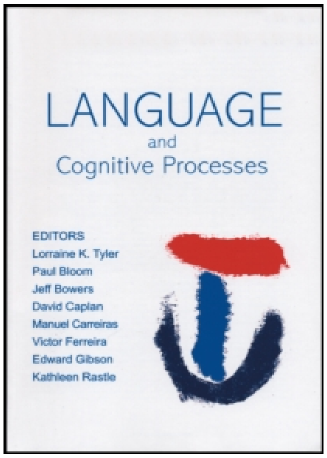

Language and Cognitive Processes
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t713683153

An evaluation of the interactive-activation model using masked partial-word priming

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Online Publication Date: 01 January 2008
To cite this Article: Perry, Jason R., Lupker, Stephen J. and Davis, Colin J. (2008) 'An evaluation of the interactive-activation model using masked partial-word priming', Language and Cognitive Processes, 23:1, 36 - 68
To link to this article: DOI: 10.1080/01690960701578112
URL: http://dx.doi.org/10.1080/01690960701578112

LANGUAGE AND COGNITIVE PROCESSES
2008, 23 (1), 36–68

Psychology Press
Taylor & Francis Group

An evaluation of the interactive-activation model using masked partial-word priming

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Predictions from Davis and Lupker's (2006) version of the interactive-activation model (McClelland & Rumelhart, 1981) were tested in four masked priming lexical decision experiments. Ambiguous partial-word primes (i.e., ho#se resembles HOUSE and HORSE) preceded word targets with few neighbours (low-N) or many neighbours (high-N) when the word/nonword discrimination was either easy (Experiment 1A) or difficult (Experiment 1B). In a second experiment, unambiguous partial-word primes (i.e., cl#ff resembles only CLIFF) preceded hermit (i.e., words with no neighbours), low-N, or high-N word targets when the word/nonword discrimination was either easy (Experiment 2A) or difficult (Experiment 2B). The model's predictions are supported by the results for the ambiguous primes, but not by the results for

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This research was supported by Natural Sciences and Engineering Research Council of Canada Grant A6333 to the second author and was submitted in partial fulfilment of the requirements for a Master's degree at the University of Western Ontario by the first author.

We would like to thank Ken Forster and Marc Brysbaert for their comments on an earlier version of this paper. Major portions of this research were presented at the 46th Annual Meeting of the Psychonomic Society, Toronto, Ontario, Canada, November, 2005, the 14th Meeting of the European Society for Cognitive Psychology, Leiden, the Netherlands, September, 2005 and the 15th Annual Meeting of the Canadian Society for Brain, Behaviour, and Cognitive Science, Montreal, Quebec, Canada, July, 2005.

http://www.psypress.com/lcp DOI: 10.1080/01690960701578112

the unambiguous primes, particularly when hermit targets are used. A revised definition of the orthographic neighbourhood of a word and/or different assumptions about the impact of frequency on lexical representations would improve the model's ability to account for the data.

An important goal of word recognition research is to develop a model of lexical retrieval. One critical variable that is thought to affect the lexical retrieval process is the nature of a word's neighbourhood (e.g., Andrews, 1997; Coltheart, Davelaar, Jonasson, & Besner, 1977; Davis, 2003; Forster & Taft, 1994; Grainger & Jacobs, 1996; Sears, Hino, & Lupker, 1995). A word's neighbourhood is typically defined as the set of words that can be created by replacing a single letter in that word (e.g., chip – ship) (Coltheart et al., 1977). The effects of a word's neighbourhood on lexical retrieval have been extensively investigated using the lexical decision task (LDT) (for a comprehensive review see Andrews, 1997).

Of particular importance to the present research are the results from studies involving formally-similar primes using Forster and Davis's (1984) masked priming paradigm. 'Form primes' that are nonwords tend to produce facilitation in an LDT (e.g., the prime 'bontrast' facilitates processing of the target CONTRAST, relative to an unrelated control prime like 'bamfleck'; Davis & Lupker, 2006; Forster & Veres, 1998) whereas form primes that are words tend to produce either null effects (Forster & Veres, 1998) or inhibition (Davis & Lupker, 2006; De Moor & Brysbaert, 2000; Grainger & Ferrand, 1994; Segui & Grainger, 1990). In addition, a 'neighbourhood density constraint' is commonly observed when nonword form primes are used, such that target words from small neighbourhoods (i.e., low-N targets) show greater facilitation than target words from large neighbourhoods (i.e., high-N targets – see Davis, 2003; Forster, 1987, 1993; Forster, Davis, Schoknecht, & Carter, 1987; Forster & Taft, 1994).

One common explanation for why the presentation of a form prime affects lexical decision latencies is that prime processing changes the activation pattern in the lexicon (Davis, 2003; Grainger & Jacobs, 1999). If so, then gaining a greater understanding of how these primes affect target processing should provide important information concerning the nature of lexical representations and processing. Thus, one important task for research in word recognition is to understand the mechanisms which cause different types of primes to have different effects on different types of targets.

McClelland and Rumelhart's (1981) interactive-activation (IA) model of lexical processing has been relatively successful in explaining data from a variety of experimental paradigms (e.g., Davis, 2003; Davis & Lupker, 2006; Grainger & Jacobs, 1993, 1996; Jacobs & Grainger, 1992; McClelland & Rumelhart, 1981). This model consists of three layers of interconnected nodes. The first layer of nodes represents features of letters. The individual letters are represented in the second layer of nodes, whereas the third layer of nodes contains whole word representations. Nodes at adjacent levels in the model are connected with both excitatory connections and inhibitory connections. Nodes at the same level are connected only by inhibitory connections.

According to the IA model, when a stimulus is presented, the features of the stimulus are activated and these features activate their corresponding letter nodes. Strongly activated letter nodes can inhibit more weakly activated letter nodes through a competitive process while at the same time activating their corresponding word nodes. As word nodes become more active they also compete with one another while, at the same time, sending feedback down to compatible letter nodes. It is through the competition among these word nodes and the feedback to the letter nodes that priming effects emerge.

Davis (2003) recently presented a computational analysis of form priming effects in the IA model, demonstrating that it is possible to derive general predictions concerning the impact of various lexical factors (e.g., neighbourhood frequency) from the model in the form of linear equations (specific predictions for a given set of words, however, require simulations involving those precise stimuli). To simulate masked priming in an LDT, Davis (2003) first set all feature, letter, and word nodes to resting levels of activation. A prime stimulus was then 'presented' by setting the binary codes at the feature level in a way that accurately represented the prime and the model was then allowed to run for a specific number of cycles. At that point, a target stimulus was 'presented' in the same manner as the prime had been (i.e., by setting binary codes at the feature level). A local activity threshold (*M* criterion) was used for word responses, set by Davis at 0.65. If the level of lexical activity for any given node passes this threshold then the simulation emits a 'word' response. Otherwise, a 'nonword' response is emitted.

Davis (2003) investigated the predictions of McClelland and Rumelhart's (1981) IA model as a function of many different prime types. For purposes of the present research, we focus on partial-word primes (e.g., Grainger & Jacobs, 1993; Hinton, Liversedge, & Underwood, 1998). A partial-word prime is a letter string in which one of the letters has been replaced by a non-alphabetic character (e.g., Grainger & Jacobs, 1993, inserted the non-alphabetic symbol '%' in various letter positions of the prime; here we used # symbols, e.g., cr#wn). Thus, in terms of Coltheart et al.'s (1977) definition of a neighbourhood, a partial-word prime could be considered a neighbour of the target (e.g., #uiz-QUIZ). There are two distinct types of partial-words that can be used as primes, unambiguous partial-word primes and ambiguous partial-word primes. According to the IA model, these two prime types will have somewhat different effects on target processing.

Unambiguous partial-word primes

A partial-word prime like cr#wn is an unambiguous partial-word prime for the target word CROWN because there are no other words that can be formed by replacing the # symbol with a letter. Davis's (2003) analysis shows that the IA model predicts a facilitatory priming effect from unambiguous primes, with the magnitude of the facilitation being determined by two factors: the degree to which the prime pre-activates the target and the degree to which the prime helps suppress the target's neighbours.

The first factor, referred to as the *target pre-activation effect*, is straightforward. Due to the fact that the prime and target overlap at n-1 letter positions, the prime pre-activates the target's lexical representation while the prime is being processed. Thus, presentation of the prime cr#wn enables the lexical representation of CROWN to be pre-activated. Critically, none of the lexical competitors of the word unit for CROWN (e.g., DROWN) are assumed to be strongly activated by these primes because DROWN and cr#wn overlap at only n-2 letter positions.

The second factor, referred to as *target neighbour suppression*, is more complicated. According to the model, when reading a word, all neighbours of that word receive some activation and, therefore, mutually inhibit each other. High-frequency neighbours of a presented word in particular, due to their higher resting activation levels, can interfere with the word's processing, especially if the word is one of low frequency. However, as noted, unambiguous partial-word primes, by definition, do not activate any of the neighbours of the target word to any real degree. That is, although CROWN has neighbours like BROWN, DROWN, and CROWD, these are not neighbours of the partial-word prime cr#wn and, hence, unambiguous partial-word primes would provide very little activation for the lexical units for these words. Presentation of an unambiguous prime therefore allows the target to get a 'head start' in processing and helps that target to suppress the competition from its neighbours. That is, because the prime cr#wn pre-activates the target CROWN, when this target is presented it can more quickly suppress the inhibition that it would ordinarily receive from its neighbours, like DROWN.

This analysis leads to the following prediction. When unambiguous partial-word primes are used, facilitatory priming should be greater for targets that have neighbours than for targets that do not have neighbours (we will refer to letter strings of the latter type as 'hermits'). The reason is that targets which are hermits only receive priming due to target pre-activation whereas targets that have neighbours benefit from both pre-activation and target neighbour suppression. Davis's (2003) simulations illustrate this prediction and also indicate that the total number of neighbours that a target word has beyond one has little impact on the size of the predicted priming effect. That is, regardless of whether the target has one neighbour or many, the presentation of an unambiguous prime will allow the target to suppress its competitor(s) to the same extent, producing equivalent size priming effects.

Ambiguous partial-word primes

Ambiguous partial-word primes are primes that are consistent with more than one word. For example, the prime #rown is consistent with the words BROWN, CROWN, DROWN, FROWN, and GROWN. Unlike unambiguous partial-word primes, ambiguous partial-word primes have both a facilitatory and an inhibitory effect on target processing.

The facilitatory priming from ambiguous partial-word primes occurs in the same manner as the facilitatory priming from unambiguous partial-word primes. That is, ambiguous primes facilitate processing through the pre-activation effect and the target neighbour suppression effect (e.g., if the target word is CROWN, the representation for the higher frequency neighbour CROWD receives little activation from the prime #rown and, hence, is more easily suppressed). The inhibitory component occurs because the prime activates shared neighbours of both the prime and the target (e.g., BROWN and CROWN are both activated by #rown). These shared neighbours become more potent target competitors due to their heightened activation, slowing target processing (Hinton et al., 1998; Van Heuven, Dijkstra, Grainger, & Schriefers, 2001). Davis (2003) refers to this phenomenon as the *shared neighbour inhibition effect*.

The modified IA model

Recently, Davis and Lupker (2006) proposed a modified IA model of masked priming. Their modifications were designed to address the problem that, in the original model, there is a relatively large inhibitory impact from unrelated primes in comparison to when no prime is presented. Davis and Lupker noted that, in the original IA model, two factors contribute to this phenomenon. One factor is a lexical factor. The assumption is that all word nodes inhibit all other word nodes, regardless of whether the two words are similar or not. Thus, low frequency target nodes, in particular, are activated more slowly when preceded by an unrelated prime than when the target is not preceded by a prime at all.

A second factor is a letter-level factor. The presentation of an unrelated prime activates a set of letter nodes that is inconsistent with the target. These inconsistent letter nodes need to be deactivated and replaced by the letter nodes of the target so that target processing can be completed successfully. It is difficult to activate the letter nodes which correspond to the target because word nodes activated by the prime continue to support the prime's letter nodes through facilitatory feedback, causing a delay in target processing (in comparison to when no prime is presented).

To deal with these two problems, Davis and Lupker (2006) made two modifications to the model. First, it was assumed that inhibition is selective. Specifically, it was assumed that a word node only sends inhibitory signals to another word node if the two words have at least one letter in the same position. For example, the word node for CLAM sends lateral inhibitory signals to word nodes for similar words like SLAP but not to word nodes for dissimilar words like DOOR. This change greatly reduces the inhibition due to unrelated primes. Second, it was assumed that all letter-level activity is immediately reset as soon as the feature level information has been overwritten. This change has the effect of eliminating the delay in target processing due to the persistence of the letter representations of the prime after the onset of the target.

EXPERIMENT 1

The goal of the present paper was to investigate the predictions of Davis and Lupker's (2006) version of the IA model concerning the influence of partial-word primes. Specifically, the effects of ambiguous (Experiment 1) and unambiguous (Experiment 2) partial-word primes on various types of word targets were explored while altering the difficulty of the word/nonword discrimination.

Experiment 1 involved both low-N (few neighbours) and high-N (many neighbours) word targets. The primes were ambiguous partial-word primes. The difficulty of the word/nonword discrimination was manipulated by using easy nonwords in one version of the experiment (Experiment 1A) and more difficult nonwords in the other version (Experiment 1B). The easy nonwords did not have any neighbours. More difficult nonwords were created by selecting half of the nonwords to have few neighbours and half to have a large number of neighbours (i.e., the nonword neighbourhood sizes matched the neighbourhood sizes of the words).

The word/nonword discrimination difficulty manipulation was modelled by varying the *M* criterion. Easier word/nonword discriminations were assumed to allow a lower value of the *M* criterion than harder word/nonword discriminations. In order to determine the importance of the criterion placement, the list of word targets preceded by their ambiguous primes was run through a version of Davis's (2003) simulator, which incorporated the changes suggested by Davis and Lupker (2006), as the *M* criterion was altered from .59 to .71. The primes were presented for 50 cycles followed immediately afterwards by the presentation of the target words.

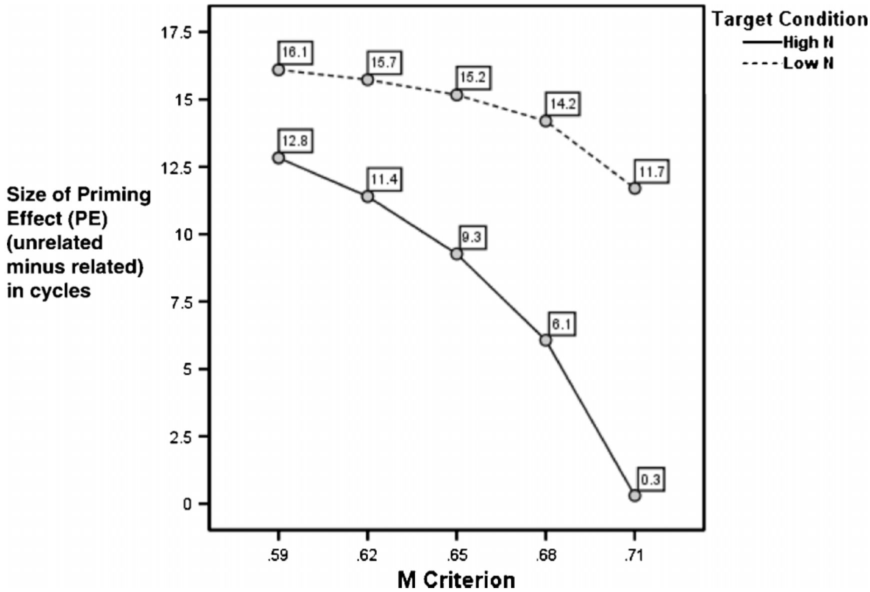

Figure 1. Predicted priming effects for ambiguous primes according to the interactive-activation model assuming letter reset and selective inhibition.

The selection of .59 for the lower boundary for the *M* criterion in the simulation was based on the fact that when the boundary was set lower than .59, the lexical activity for the words in both related and unrelated conditions reached the *M* criterion too quickly to show any priming effects. An upper boundary for the *M* criterion of .71 was selected based on the fact that when the *M* criterion was set higher than .71, the lexical activity for many of the words no longer reached criterion. This failure to reach higher criterion values is due to the fact that competitors had the time to create sufficient inhibition to cause word node activity levels to asymptote below the criterion value. With values between .59 and .71 all the word nodes reached criterion.

The predicted priming effects for the word targets in Experiment 1 (in cycles) are depicted in Figure 1 (these values are computed by subtracting the latency for word targets preceded by an ambiguous related prime from the corresponding latency for the same target preceded by an unrelated prime). Three specific predictions can be made based upon this analysis. First, high-N word targets are predicted to show less facilitation than low-N word targets regardless of the word/nonword discrimination difficulty

(Forster et al.'s., 1987, neighbourhood density constraint).[1] Second, as the word/nonword discrimination becomes more difficult the size of the priming effect for both low-N and high-N word targets should decrease. Third, the difference in the size of the priming effect between high-N and low-N word targets should increase as the word/nonword discrimination difficulty increases.

Experiment 1A

Method

Participants. Forty University of Western Ontario psychology undergraduate students received $10 for their participation in this study. All had either normal or corrected-to-normal vision and were proficient in English. Their ages ranged from 18–53 with a median age of 21.

Materials. Sixty word targets and 60 nonword targets were selected. All stimuli were five letters in length. The 60 word targets (see the Appendix) consisted of an equal number of low-N ($N = 1$ or 2 with a mean of 1.53), and high-N targets ($N = 5$–8 with a mean of 6.17). Neighbourhood size was determined through the use of Davis's (2005) N-Watch program. The average Kucera and Francis (1967) frequency was 22.93 (range = 1–58) for the low-N word targets and 22.37 (range = 2–61) for the high-N word targets. Average CELEX frequencies (Baayen, Pipenbrock, & van Rijn, 1995) were 23 (range = 1–93) for the low-N word targets, and 26 (range = 3–79) for the high-N word targets. The 60 nonword targets were all orthographically legal and pronounceable hermit ($N = 0$) nonwords. (All the nonwords in these experiments were orthographically legal, pronounceable nonwords taken from previously published studies.)

For each word target, a partial-word prime was created by replacing one of the letters in the target with a # such that at least two words could be created by replacing the # with a letter. For example, the partial-word prime #rown can be made into the word 'brown' by replacing the # with a 'b' or the word 'crown' by replacing the # with a 'c'. Related primes were created for each of the 30 low-N word targets ($N = 2$ or 3 with a mean of 2.2) and each of the 30 high-N word targets ($N = 2$–6 with a mean of 3.4). The position that was replaced was equated as much as possible across the word targets in the two experiments. For high-N word targets, the letter in position 1 was replaced in 7 primes, the letter in position 2 in 6 primes, the letter in position

[1] At least part of the reason that the model predicts a neighbourhood density constraint is that high-N targets have more shared neighbours with their related ambiguous primes than low-N targets. Across the 60 targets in Experiment 1, the correlation between N and the number of shared neighbours was $r = .59$, $t(58) = 5.58$, $p < .001$.

3 in 5 primes, the letter in position 4 in 4 primes and the letter in position 5 in 8 primes. For low-N word targets, the letter in position 1 was replaced in 11 primes, the letter in position 2 was replaced in 4 primes, the letter in position 3 was replaced in 3 primes, the letter in position 4 was replaced in 3 primes and the letter in position 5 was replaced in 9 primes. For each nonword target, a related prime was created by replacing one of the letters in the nonword with a # symbol. The distribution of positions was the same as for the primes for the high-N word targets.

For any given participant, half the word and half the nonword targets were preceded by their related primes and the remaining word and nonword targets were preceded by unrelated primes. The unrelated prime-target pairs were created by re-pairing the related primes for each of these targets subject to the condition that unrelated primes and their word targets did not begin with the same letter. In order for each target to appear in both the related and unrelated conditions, two lists of stimuli were created, each containing 60 related and 60 unrelated trials. If a target was preceded by a related prime in one list, it was preceded by an unrelated prime in the other list. Each list was presented to half the participants.

Equipment. All experiments were run using DMDX experimental software produced by Forster and Forster (2003). Stimuli were presented on a SyncMaster monitor (Model No. 753DF). Presentation was controlled by an IBM-clone Intel Pentium. Stimuli appeared as black characters on a white background. Responses to stimuli were made by pressing one of two <shift> keys on the keyboard.

Procedure. Participants were run individually. Each participant sat approximately 18 inches in front of the computer screen and was told by the experimenter to respond to strings of letters presented on the computer screen by pressing one key (the right <shift> key) if the item was a word or another key (the left <shift> key) if the item was not a word. The participants were told that a string of number signs (i.e., '#####') would appear followed by a string of letters which they were required to respond to, but they were not told of the existence of the prime. They were also told to respond to each target as quickly and as accurately as possible.

On each trial the participants saw the string of number signs (e.g., '#####') for 590 ms followed by the presentation of the partial-word prime for 60 ms in lower case letters. The target string then appeared in upper case letters for either 3 s or until the participant responded.

Participants performed five practice trials before beginning the experiment and were given the opportunity both during the practice trials and immediately afterwards to ask the experimenter any questions in order to clarify any confusion concerning what was required. For each practice trial,

TABLE 1
Results for easy nonwords and ambiguous primes (Experiment 1A – reaction times in milliseconds, errors in percent)

	Error rate		*Reaction time*		
Target size	*Unrelated*	*Related*	*Unrelated*	*Related*	*Priming effect*
Words					
Low-N	1.8 (4.0)	2.2 (3.8)	584 (86)	554 (88)	30
High-N	2.7 (5.8)	1.7 (3.3)	573 (93)	562 (95)	11
Nonwords	2.7 (5.8)	1.7 (3.3)	706 (168)	706 (171)	0

Note. Numbers in parentheses are the standard deviations.

the experimenter provided feedback as to whether or not the participant responded correctly.

Results

Incorrect responses were removed from the latency analyses. Also removed were latencies shorter than 250 ms or longer than 2000 ms (2.2% of the word trials, 6.5% of the nonword trials). The data were submitted to a 2 (relatedness: related vs. unrelated) $\times$ 2 (target neighbourhood size: low-N vs. high-N) analysis of variance (ANOVA). Subject (F_1) and item (F_2) ANOVAs were performed on both reaction time and accuracy. Paired sample t-tests were also performed to examine the relatedness effect for the nonword data based on either subjects (t_1) or items (t_2). The mean reaction times and error rates from the subject analysis are presented in Table 1.[2]

RT analyses. For the word data there was a significant main effect of relatedness, $F_1(1, 39) = 12.48$, $p < .001$; $F_2(1, 58) = 4.33$, $p < .04$. Word targets were responded to faster when preceded by a related prime (558 ms) than when preceded by an unrelated prime (579 ms). There was no main effect of target neighbourhood size, $F_1(1, 39) = 0.03$, *ns*; $F_2(1, 58) = 0.05$, *ns*. The interaction of relatedness and target neighbourhood size was also non-significant, $F_1(1, 39) = 2.28$, *ns*; $F_2(1, 58) = 0.73$, *ns*.

[2] A few of the primes formed words if the # is removed (e.g., ho#se). In order to determine whether these primes produced different priming patterns than primes with the # in a different position, the latency analyses were re-run after excluding all word targets that were preceded by a prime that formed a word if the # was removed, on either related or unrelated trials. A total of six low-N words targets and eight high-N word targets were excluded. None of the important findings of Experiment 1A or 1B changed in this analysis.

The effect of relatedness for the nonword latencies was not significant, $t_1(39) = 0.12$, *ns*; $t_2(59) = 0.25$, *ns.*

Error analysis. The analysis of errors for the word data revealed no significant main effects or interactions (all Fs < 1.52). The effect of relatedness for the nonword accuracy data was also not significant, $t_1(39) = 0.41$, *ns*; $t_2(59) = 0.43$, *ns.*

Experiment 1B

Method

Participants. Forty University of Western Ontario psychology undergraduate students received $10 for their participation in this study. All had either normal or corrected-to-normal vision and were proficient in English. Their ages ranged from 18–61 with a median age of 22.

Materials. The word targets were the same as in Experiment 1A. The only change was to the nonword stimuli. The 60 nonword targets consisted of 30 low-N nonwords (N = 1 or 2 with a mean of 1.4) and 30 high-N nonwords (N = 5–8 with a mean of 5.9). Related primes for each of the 30 low-N nonword targets (N = 1 or 2 with a mean of 1.2) and 30 high-N nonword targets (N = 1–6 with a mean of 2.2) were created.

All other materials and equipment were the same as in Experiment 1A.

Procedure. The procedure was the same as in Experiment 1A.

Results

Incorrect responses were removed from the latency analyses. Also removed were latencies shorter than 250 ms or longer than 2000 ms (3.6% of the word trials, 10.5% of the nonword trials). The data for both the words and the nonwords were submitted to a 2 (relatedness: related vs. unrelated) by 2 (target neighbourhood size: low-N vs. high-N) ANOVA. Subject (F_1) and item (F_2) ANOVAs were performed on both reaction time and accuracy. The mean reaction times and error rates from the subject analysis are presented in Table 2.

RT analyses. For the word data there was a marginal effect of relatedness in the subject analysis, $F_1(1, 39) = 3.72$, $p < .06$, and a significant effect in the item analysis, $F_2(1, 58) = 4.36$, $p < .04$. Word targets were responded to faster when preceded by a related prime (599 ms) than when preceded by an unrelated prime (611 ms). The main effect for target neighbourhood size was not significant, $F_1(1, 39) = 0.57$, *ns*; $F_2(1, 58) = 0.12$, *ns,* nor was the

TABLE 2
Results for hard nonwords and ambiguous primes (Experiment 1B – reaction times in milliseconds, errors in percent)

	Error rate		*Reaction time*		
Target size	*Unrelated*	*Related*	*Unrelated*	*Related*	*Priming effect*
Words					
Low-N	3.8 (5.2)	3.5 (5.4)	615 (71)	598 (80)	17
High-N	4.2 (5.4)	2.5 (4.2)	606 (66)	599 (70)	7
Nonwords					
Low-N	7.3 (9.3)	8.5 (10.1)	754 (165)	744 (177)	10
High-N	9.8 (13.8)	12.0 (14.1)	780 (158)	770 (184)	10

Note. Numbers in parentheses are the standard deviations.

interaction of relatedness and target neighbourhood size, $F_1(1, 39) = 0.94$, *ns*; $F_2(1, 58) = 0.45$, *ns*.

For the nonword data there was no significant main effect of relatedness, $F_1(1, 58) = 1.06$, *ns*; $F_2(1, 58) = 0.81$, *ns*. However, there was a significant main effect of target neighbourhood size, $F_1(1, 39) = 11.87$, $p < .001$, which was marginal in the item analysis, $F_2(1, 58) = 2.91$, $p < .09$. Low-N nonword targets (749 ms) were responded to faster than high-N nonword targets (775 ms). The interaction was not significant, $F_1(1, 39) = 0.01$, *ns*; $F_2(1, 58) = 0.09$, *ns*.

Error analysis. The analysis of errors for the word data revealed no significant main effects or interactions (all Fs < 1.90).

For the nonword data, there was no significant main effect of relatedness, $F_1(1, 39) = 2.05$, *ns*; $F_2(1, 58) = 1.97$, *ns*. However, there was a significant main effect of target neighbourhood size in the subject analysis, $F_1(1, 39) = 6.60$, $p < .01$, which was marginal in the item analysis, $F_2(1, 58) = 2.85$, $p < .10$. The error rate was greater for high-N nonword targets (10.9%) than for low-N nonword targets (7.9%). The interaction was not significant, $F_1(1, 39) = 0.14$, *ns*; $F_2(1, 58) = 0.18$, *ns*.

Combined analysis for ambiguous primes

To analyse the effect of nonword difficulty across the two ambiguous prime experiments two combined ANOVAs, one based on the word data and one based on the nonword data, were performed. The word data were submitted to a 2 (relatedness: related vs. unrelated) by 2 (target neighbourhood size: low-N vs. high-N) by 2 (nonword difficulty: easy vs. hard) ANOVA. The nonword data were submitted to a 2 (relatedness: related vs. unrelated) by

2 (nonword difficulty: easy vs. hard) ANOVA. Subject (F_1) and item (F_2) ANOVAs were performed for both reaction time and accuracy.

RT analyses. For the word data, the main effects of relatedness, $F_1(1, 78) = 14.77$, $p < .001$; $F_2(1, 116) = 8.25$, $p < .005$, and nonword difficulty, $F_1(1, 78) = 4.68$, $p < .03$; $F_2(1, 116) = 16.77$, $p < .001$, were significant. The nonword difficulty effect indicates that word latencies were significantly slower when harder nonwords were used. None of the interactions were significant. The interaction between relatedness and target neighbourhood size approached significance in the subject analysis, $F_1(1, 78) = 3.20$, $p < .10$, but not the item analysis, $F_2(1, 116) = 1.17$, *ns.* This marginal interaction reflects the fact that the priming effects tended to be greater for low-N targets than for high-N targets (i.e., the density constraint).

For the nonword data there was no main effect of relatedness, $F_1(1, 78) = 0.32$, *ns*; $F_2(1, 118) = 0.08$, *ns.* There was a main effect of nonword difficulty, $F_1(1, 78) = 13.31$, $p < .001$; $F_2(1, 118) = 27.01$, $p < .001$. Latencies for the nonwords were slower when harder nonwords were used. The interaction was not significant, $F_1(1, 78) = 0.53$, *ns*; $F_2(1, 118) = 0.48$, *ns.*

Error analyses. For words, the main effect of nonword difficulty was significant in the subject analysis, $F_1(1, 78) = 4.79$, $p < .03$, but not in the item analysis, $F_2(1, 116) = 2.63$, *ns.* More errors were made to words when hard nonwords were used than when easy nonwords were used. No other effects were significant (all Fs < 2.50).

For nonwords, the main effect of relatedness was not significant, $F_1(1, 78) = 0.17$, *ns*; $F_2(1, 118) = 0.67$, *ns.* The main effect of nonword difficulty was not significant in the subject analysis, $F_1(1, 78) = 1.89$, *ns*, but it was in the item analysis, $F_2(1, 118) = 10.92$, $p < .001$. The interaction was not significant, $F_1(1, 78) = 0.76$, *ns*; $F_2(1, 118) = 1.86$, *ns.*

Participants were significantly slower to respond and more error prone for both words and nonwords in Experiment 1B than in Experiment 1A. These results indicate that the word/nonword discrimination in Experiment 1B was significantly more difficult than in Experiment 1A and, therefore, participants presumably adopted a more conservative response criterion placement in Experiment 1B than in Experiment 1A. In the IA framework discussed here, this would correspond to the use of a higher *M* criterion in Experiment 1B than in Experiment 1A.

Discussion

When the word/nonword discrimination was easy (Experiment 1A) there was significant priming overall. Also, low-N word targets showed noticeably more priming (30 ms) than high-N word targets (11 ms). Although this 19 ms advantage for low-N word targets was not significant, it is consistent with Davis's (2003) prediction that low-N word targets would receive greater benefit from the presentation of an ambiguous prime than high-N word targets. It is also consistent with Forster and colleagues' (Forster, 1987, 1993; Forster et al., 1987; Forster & Taft, 1994) results showing larger priming effects for low-N word targets (the 'density constraint').

When the difficulty of the word/nonword discrimination was increased by using an equal number of low-N and high-N nonwords (Experiment 1B), the model predicted that the size of the priming effects would decrease. Numerically, this prediction was supported, as the priming effects for both low-N word targets and high-N word targets were noticeably smaller when more difficult nonwords were used (17 ms and 7 ms, respectively) than when easier nonwords were used (30 ms and 11 ms, respectively).

The model also predicted that the difference in the size of the priming effects between low-N and high-N word targets would increase as the difficulty of the word/nonword discrimination increased. There is no evidence to support this prediction and, in fact, the difference in the size of the priming effect when the word/nonword discrimination was easy (19 ms) was actually larger than the difference when harder nonwords were used (10 ms).

At a general level, a decrease in the size of the priming effect when more difficult nonwords are used may seem somewhat surprising. A more standard result when the difficulty of the word/nonword discrimination is increased is that effect sizes either increase (Pexman, Lupker, & Jared, 2001; Pexman, Lupker, & Reggin, 2002; Stone & Van Orden, 1993) or remain constant (Perea & Lupker, 2003a), although see Forster and Veres (1998) for an exception. The fact that this version of the IA model predicted the observed decrease in the size of the priming effect is an additional source of support for the model.

EXPERIMENT 2

Experiment 2 was similar to Experiment 1 except that now unambiguous primes were used and hermit word targets were added to the target set. Simulations for these stimuli were generated using Davis and Lupker's (2006) version of the IA model and by varying the value of the *M* criterion. Two specific predictions were derived from these simulations (see Figure 2). First, low-N and high-N word targets should always receive greater benefit from the presentation of an unambiguous prime than hermit word targets regardless of the word/nonword discrimination difficulty. (As discussed earlier, this difference is due to the lack of a target neighbour suppression effect for hermit targets.) Second, and more importantly, the amount of priming for both hermit and high-N word targets should remain relatively constant as the word/nonword discrimination difficulty increases, however, the amount of priming obtained for low-N word targets should increase as the word/nonword discrimination difficulty increases.

This prediction for low-N targets may seem somewhat counter-intuitive, however, it does follow from an analysis of what happens in the model. In essence, the predicted increase in the size of the priming effect with the change from easy to hard nonwords is due to the fact that word targets with few neighbours have only a few competitors that need to be suppressed. With just a few neighbours, an unambiguous related prime can allow the target to quickly suppress all the neighbours that might compete with it. Thus, a related prime will allow the target to essentially escape inhibitory influences at some point in processing. From that point on, processing will be quite rapid. With a high criterion setting, as would be the case with hard nonwords, related primes can then produce a much larger advantage over unrelated primes than with easy nonwords (i.e., when the criterion setting is low). In essence, once the target neighbours are sufficiently suppressed, it is clear sailing to the finish line.

In contrast, neither hermits nor high-N word targets benefit in this way. Hermits will not show this pattern because, as noted, they have no

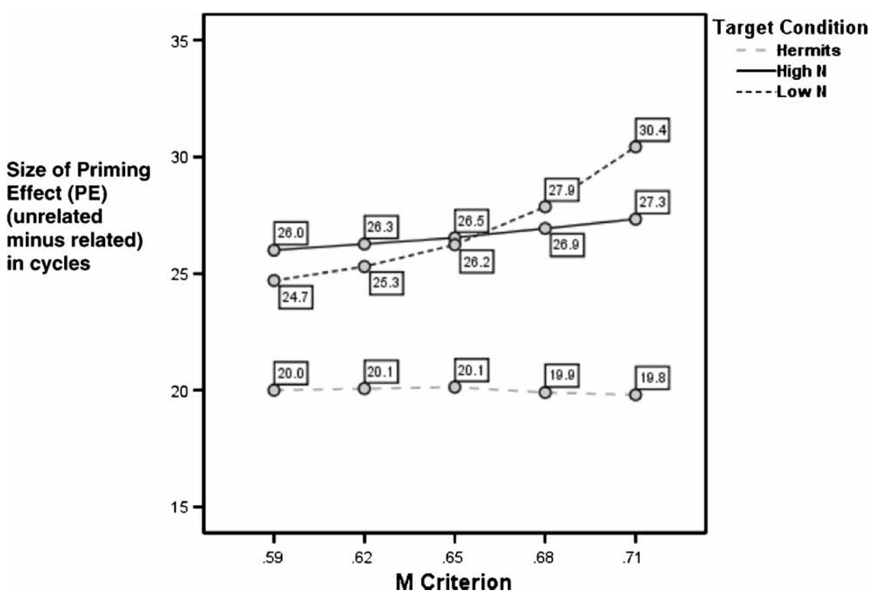

Figure 2. Predicted priming effects for unambiguous primes according to the interactive-activation model assuming letter reset and selective inhibition.

neighbours to suppress. The head start provided by a related prime will merely maintain itself regardless of where the finish line (i.e., the criterion) is set. High-N target words have a different problem. For them, there are so many competitors (i.e., neighbours) that they never break free of them. Thus, the size of the advantage for related primes over unrelated primes stays constant over changes in criterion placement.

These predictions were tested in two experiments. In one experiment (Experiment 2A) the word/nonword discrimination was easy, while in the other experiment (Experiment 2B) the word/nonword discrimination was made more difficult by using nonwords with neighbourhood sizes that matched those of the word targets.

Experiment 2A

Method

Participants. Forty University of Western Ontario psychology undergraduate students received $10 for their participation in this study. All had either normal or corrected-to-normal vision and were proficient in English. Their ages ranged from 17–40 with a median age of 18.

Materials. Ninety word targets (see Appendix) and ninety nonword targets were selected. All stimuli were five letters in length. The 90 word targets consisted of an equal number of hermit (N = 0), low-N, and high-N targets. The low-N and high-N word targets were the same as those used in Experiment 1. The hermit targets were matched to the low-N and high-N targets on frequency (Kucera & Francis, 1967). The average frequency for hermits was 22.43 (range = 1–76), the average low-N target frequency was 22.93 (range = 1–58), and the average high-N target frequency was 22.37 (range = 2–61). Average CELEX frequencies (Baayen et al., 1995) were 17 (range = 1–59) for the hermit word targets, 23 (range = 1–93) for the low-N word targets, and 26 (range = 3–79) for the high-N word targets. The 90 nonword targets consisted of both hermits and a few low-N targets (N = 0 or 1 with a mean of 0.23). The hermit nonwords were the same as those used in Experiment 1A and the low-N nonwords were some of those used in Experiment 1B.

For each word target, a related prime was created by replacing one of the letters in the prime with a #. The crucial aspect of these primes is that the replaced letter is the only letter that could be inserted into that position in the letter string in order to create a word (e.g., in the letter string #igar, which is the prime for CIGAR, ‘c’ is the only letter that can be substituted for the #

to form a word). The distribution of replaced positions was the same for all three types of word targets (and the same as for the high-N targets in Experiment 1). The letter in position 1 was replaced in 7 primes, the letter in position 2 in 6 primes, the letter in position 3 in 5 primes, the letter in position 4 in 4 primes and the letter in position 5 in 8 primes. Related primes were also created for the nonword targets, by replacing one letter of each target with a #.

For any given participant, half the word and half the nonword targets were preceded by their related primes and the remaining word and nonword targets were preceded by unrelated primes. As in Experiment 1, unrelated prime-target pairs were created by re-pairing the related primes for these targets. In order for each target to appear in both the related and unrelated conditions, two lists of stimuli were created which contained 90 related and 90 unrelated trials. If a target was preceded by a related prime in one list, it was preceded by an unrelated prime in the other list. Each list was presented to half the participants.

Procedure. The procedure was the same as in Experiment 1A.

Results

Incorrect responses were removed from the latency analyses. Also removed were latencies shorter than 250 ms or longer than 2000 ms (3.2% of the word data, 7.7% of the nonword data). The data were submitted to a 2 (relatedness: related vs. unrelated) $\times$ 3 (target neighbourhood size: hermit vs. low-N vs. high-N) ANOVA. Subject (F_1) and item (F_2) ANOVAs were performed on both reaction time and accuracy. Paired sample t-tests were also performed to examine the relatedness effect for the nonword data based on both subjects (t_1) and items (t_2). The mean reaction times and error rates from the subject analysis are presented in Table 3.[3]

RT analyses. For the word data there was a significant main effect of relatedness, $F_1(1, 39) = 20.41$, $p < .001$; $F_2(1, 87) = 29.0$, $p < .001$. Word

[3] As in Experiment 1, a few of the primes formed words if the # is removed (e.g., #loud). In order to determine whether these primes produced different priming patterns than primes with the # in a different position, the latency analyses were re-run after excluding all word targets that were preceded by a prime which formed a word if the # was removed, on either related or unrelated trials. This led to the removal of two hermit, ten low-N, and nine high-N word targets. As in Experiment 1, this did not change any of the important findings. Hermit word targets still produced essentially the same amount of priming as the other words when easy nonwords were used (Experiment 2A) and still received the largest benefit from the prime when more difficult nonwords were used (Experiment 2B).

TABLE 3
Results for easy nonwords and unambiguous primes (Experiment 2A – reaction times in milliseconds, errors in percent)

	Error rate		*Reaction time*		
Target size	*Unrelated*	*Related*	*Unrelated*	*Related*	*Priming effect*
Words					
Hermits	6.3 (7.2)	3.7 (6.4)	619 (65)	595 (74)	24
Low-N	2.8 (5.0)	2.7 (4.5)	576 (62)	547 (62)	29
High-N	1.5 (3.2)	0.8 (2.2)	566 (54)	539 (51)	27
Nonwords	7.7 (8.4)	6.9 (7.6)	694 (109)	683 (119)	11

Note. Numbers in parentheses are the standard deviations.

targets were responded to faster when preceded by a related prime (560 ms) than when preceded by an unrelated prime (587 ms). There was also a significant main effect of target neighbourhood size, $F_1(2, 78) = 60.88$, $p <$ .001; $F_2(2, 87) = 8.83$, $p < .001$ The interaction was not significant, $F_1(2, 78) = 0.04$, *ns*; $F_2(2, 87) = 0.04$, *ns*.

Post hoc *t*-tests were used to examine the significant main effect of target neighbourhood size for words. High-N word targets (552 ms) were responded to significantly faster than hermit word targets (606 ms), $t_1(39) = 11.85$, $p < .001$; $t_2(58) = 3.73$, $p < .001$, and marginally faster than low-N word targets (561 ms), $t_1(39) = 1.90$, $p < .07$; $t_2(29) = 1.17$, *ns*. Low-N word targets were responded to significantly faster than hermit word targets, $t_1(39) = 6.96$, $p < .001$; $t_2(29) = 2.71$, $p < .01$.

For the nonword data the main effect of relatedness was not significant $t_1(39) = 1.64$, *ns*; $t_2(39) = 1.05$, *ns*.

Error analyses. For the word data there was a marginal effect of relatedness, $F_1(1, 39) = 2.79$, $p < .10$; $F_2(1, 87) = 3.68$, $p < .06$. Error rates were greater for targets preceded by an unrelated prime (3.6%) than for targets preceded by a related prime (2.4%). The main effect of target neighbourhood size was significant in the subject analysis, $F_1(2, 78) = 12.82$, $p < .001$, and marginal in the item analysis, $F_2(2, 87) = 2.92$, $p < .06$. The error rate was greater for hermit word targets (5.0%) than for either low-N word targets (2.8%) or high-N word targets (1.2%). The interaction was not significant, $F_1(2, 78) = 1.78$, *ns*; $F_2(2, 87) = 1.58$, *ns*.

For the nonword data the main effect of relatedness was not significant $t_1(39) = 0.93$, *ns*; $t_2(89) = 0.77$, *ns*.

Experiment 2B

Method

Participants. Sixty University of Western Ontario psychology undergraduate students participated in this experiment. Half of them received $10 for their participation and half received course credit. All of them had either normal or corrected-to-normal vision and were proficient in English. Their ages ranged from 17–53 with a median age of 19.

Materials. The word targets were the same as in Experiment 2A. The 90 nonword targets consisted of 30 hermit (N = 0), 30 low-N (N = 1 or 2 with a mean of 1.4), and 30 high-N (N = 5–8 with a mean of 5.9) nonwords.

All other materials and equipment were the same as in Experiment 2A.

Procedure. The procedure was the same as in Experiment 1A.

Results

Incorrect responses were removed from the latency analyses. Also removed were latencies that were shorter than 250 ms or longer than 2000 ms (4.8% of the word data, 11.6% of the nonword data). The data for both the words and the nonwords were submitted to a 2 (relatedness: related vs. unrelated) × 3 (target neighbourhood size: hermit vs. low-N vs. high-N) ANOVA. Subject (F_1) and item (F_2) ANOVAs were performed on both reaction time and accuracy. The mean reaction times and error rates from the subject analysis are presented in Table 4.

RT analyses. For the word data there was a significant main effect of relatedness, $F_1(1, 59) = 46.36$, $p < .001$; $F_2(1, 87) = 35.80$, $p < .001$. Word targets were responded to faster when preceded by a related prime (591 ms) than when preceded by an unrelated prime (627 ms). There was also a main effect of target neighbourhood size, $F_1(2, 118) = 34.06$, $p < .001$; $F_2(2, 87) = 5.59$, $p < .01$. The interaction was not significant, $F_1(2, 118) = 1.91$, *ns*; $F_2(2, 87) = 2.16$, *ns*.

Post hoc t-tests were performed to examine the main effect of target neighbourhood size for words. High-N word targets (594 ms) were responded to significantly faster than hermit word targets (636 ms), $t_1(59) = 6.06$, $p < .001$; $t_2(58) = 2.87$, $p < .01$, but not significantly faster than low-N word targets (598 ms), $t_1(59) = 0.82$, *ns*; $t_2(29) = 0.48$, *ns*. Low-N word targets were responded to significantly faster than hermit word targets, $t_1(59) = 7.68$, $p < .001$; $t_2(58) = 2.38$, $p < .03$.

TABLE 4
Results for hard nonwords and unambiguous primes (Experiment 2B – reaction times in milliseconds, errors in percent)

	Error rate		*Reaction time*		
Target size	*Unrelated*	*Related*	*Unrelated*	*Related*	*Priming effect*
Words					
Hermits	8.9 (12.9)	6.1 (8.7)	661 (119)	610 (85)	51
Low-N	3.7 (5.8)	4.4 (6.5)	612 (90)	583 (83)	29
High-N	3.3 (5.2)	3.2 (4.4)	608 (87)	580 (89)	28
Nonwords					
Hermits	7.1 (7.8)	6.3 (9.9)	730 (155)	725 (160)	5
Low-N	8.6 (9.8)	8.8 (13.0)	761 (180)	759 (175)	2
High-N	16.9 (16.8)	18.1 (16.3)	805 (171)	793 (155)	12

Note. Numbers in parentheses are the standard deviations.

For the nonword data there was no significant main effect of relatedness, $F_1(1, 59) = 0.79$, *ns.*; $F_2(1, 87) = 1.72$, *ns.* There was a significant main effect for target neighbourhood size, $F_1(2, 118) = 43.08$, $p < .001$; $F_2(2, 87) = 14.00$, $p < .001$. The interaction was not significant, $F_1(2, 118) = 0.24$, *ns*; $F_2(2, 87) = 0.14$, *ns.*

Post hoc *t*-tests were performed to examine the main effect of target neighbourhood size for nonwords. Hermit nonword targets (728 ms) were responded to significantly faster than high-N nonword targets (799 ms), $t_1(59) = 8.69$, $p < .001$; $t_2(58) = 5.00$, $p < .001$, and low-N nonword targets (760 ms), $t_1(59) = 4.87$, $p < .001$; $t_2(58) = 2.54$, $p < .02$. Low-N nonword targets were responded to significantly faster than high-N nonword targets, $t_1(59) = 4.79$, $p < .001$; $t_2(58) = 2.77$, $p < .01$.

Error analyses. For the word data there was no main effect of relatedness, $F_1(1, 59) = 0.72$, *ns*; $F_2(1, 87) = 0.39$, *ns.* There was a main effect for target neighbourhood size in the subject analysis, $F_1(2, 118) = 11.67$, $p < .001$, but not in the item analysis, $F_2(2, 87) = 1.77$, *ns.* Hermit word targets (7.5%) had a higher error rate than either low-N word targets (4.1%) or high-N word targets (3.2%). The interaction was not significant, $F_1(2, 118) = 2.20$, *ns*; $F_2(2, 87) = 0.89$, *ns.*

For the nonword data there was no main effect of relatedness, $F_1(1, 59) = 0.09$, *ns*; $F_2(1, 87) = 0.08$, *ns.* The main effect for target neighbourhood size was significant, $F_1(2, 118) = 46.14$, $p < .001$; $F_2(2, 87) = 19.31$, $p < .001$. High-N nonword targets (17.5%) had higher error rates than either hermit nonword targets (6.7%) or low-N nonword targets (8.7%). The interaction was not significant, $F_1(2, 118) = 0.54$, *ns*; $F_2(2, 87) = 0.54$, *ns.*[4]

Combined analysis for unambiguous primes

To analyse the effect of nonword difficulty across the two unambiguous prime experiments, two combined ANOVAs, one based on the word data and one based on the nonword data were performed. The word data were submitted to a 2 (relatedness: related vs. unrelated) × 3 (target neighbourhood size: hermit vs. low-N vs. high-N) × 2 (nonword difficulty: easy vs. hard) ANOVA. The nonword data were submitted to a 2 (relatedness: related vs. unrelated) × 2 (nonword difficulty: easy vs. hard) ANOVA. Subject (F_1) and item (F_2) ANOVAs were performed for both reaction time and accuracy.

RT analyses. For the word data, all three main effects were significant: the main effect of target neighbourhood size, $F_1(2, 196) = 83.17$, $p < .001$; $F_2(2, 174) = 14.21$, $p < .001$, the main effect of relatedness, $F_1(1, 98) = 60.25$, $p < .001$; $F_2(1, 174) = 64.60$, $p < .001$, and the main effect of nonword

[4] An additional post-hoc analysis was conducted to examine whether the results in either experiment could have been affected by the position of the letter that was replaced by a # in the prime. In particular, we wished to look at the impact of replacing the first letter on the size of the priming effects. Research suggests that the first letter in a word may be particularly important for word identification (e.g., Bruner & O'Dowd, 1958; Davis, Perea, & Acha, 2007; Perea, 1998). Thus, primes that do not have their first letter (e.g., #ovie-MOVIE) may be less effective than other primes. This possibility is particularly relevant to Experiment 1 because there was a small difference between the low-N target condition and the high-N target condition in the number of first-letter replacement primes (19 of 30 low-N word targets were preceded by related primes which began with a letter and 23 of 30 high-N word targets were preceded by related primes which began with a letter).

To determine if the presence of the first letter of the target word in the prime affects the size of the priming effect, the word targets in both experiments were divided into two groups: those that had a letter in the first position of the prime and those which had a # in the first position of the prime. For Experiments 1A and 1B, 2 (target neighbourhood size: low-N vs. high-N) × 2 (relatedness: related vs. unrelated) × 2 (prime first position: letter vs. symbol) ANOVAs were run. For Experiments 2A and 2B, 3 (target neighbourhood size: hermit vs. low-N vs. high-N) × 2 (relatedness: related vs. unrelated) × 2 (prime first position: letter vs. symbol) ANOVAs were run. The most important finding of these analyses was that none of the interactions with prime first position were significant. Priming effects were not, in general, larger for related primes that maintained their first letter. In 5 of the 10 possible comparisons, primes with a # in the first letter position provided more priming than primes having their first letter. In only 3 of the 10 comparisons, did primes with first letters provide more priming than primes with a # in the first letter position. In essence, this analysis suggests that this factor is of limited importance. Certainly, there is essentially no evidence that one should be concerned that the small difference between the low-N condition (19 of 30 related primes with a letter in the first letter position) and the high-N condition (23 of 30 related primes with a letter in the first letter position) might have artefactually affected the results in Experiment 1.

difficulty, $F_1(1, 98) = 5.95$, $p < .02$; $F_2(1, 174) = 15.62$, $p < .001$. None of the interactions were significant (all Fs < 1.65).

For the nonword data there was a marginally significant main effect of relatedness in the subject analysis, $F_1(1, 98) = 2.90$, $p < .09$, but not in the item analysis, $F_2(1, 178) = 2.63$, *ns.* The main effect of nonword difficulty was significant, $F_1(1, 98) = 6.63$, $p < .01$; $F_2(1, 178) = 60.18$, $p < .001$. The interaction was not significant, $F_1(1, 98) = 0.24$, *ns*; $F_2(1, 178) = 0.01$, *ns.*

Error analyses. For the word data, the only interaction that approached significance was the interaction between target neighbourhood size and relatedness which was significant in the subject analysis, $F_1(2, 196) = 3.20$, $p < .04$, and marginal in the item analysis, $F_2(2, 174) = 2.30$, $p < .10$. (All other interactions had F values less than 0.50.) The main effect of relatedness was not significant, $F_1(1, 98) = 2.53$, *ns*; $F_2(1, 174) = 2.81$, *ns.* The main effect of nonword difficulty was significant in the subject analysis, $F_1(1, 98) = 4.52$, $p < .04$, but not in the item analysis, $F_2(1, 174) = 1.66$, *ns.* The main effect of target neighbourhood size was also significant, $F_1(2, 196) = 21.37$, $p < .001$; $F_2(2, 174) = 4.47$, $p < .01$.

For the nonword data there was no main effect of relatedness, $F_1(1, 98) = 0.24$, *ns*; $F_2(1, 178) = 0.19$, *ns.* However, the main effect of nonword difficulty was significant, $F_1(1, 98) = 3.86$, $p < .05$; $F_2(1, 178) = 8.83$, $p < .005$. The interaction was not significant, $F_1(1, 98) = 0.79$, *ns*; $F_2(1, 178) = 0.61$, *ns.*

Participants were significantly slower to respond and more error prone for both words and nonwords in Experiment 2B than in Experiment 2A. These results indicate that the word/nonword discrimination in Experiment 2B was significantly more difficult than in Experiment 2A and, therefore, participants presumably adopted a more conservative response criterion in Experiment 2B than in Experiment 2A. In the IA framework examined here, this would correspond to the use of a higher M criterion in Experiment 2B than in Experiment 2A.

Discussion

In Experiment 2A, the word/nonword discrimination was relatively easy (because the nonwords had either few or no neighbours) and robust priming was observed. However, unlike in Experiment 1, the data did not mirror the predicted patterns. Although the size of the priming effect for both low-N (29 ms) and high-N word targets (27 ms) was slightly greater than that for hermit word targets (24 ms) this difference is much smaller than expected. Note also that there was little difference in the size of the priming effect for low-N versus high-N word targets, as expected (see Figure 2).

In Experiment 2B, the difficulty of discriminating words and nonwords was increased by using an equal number of hermit, low-N, and high-N nonwords. Strong priming was also observed in this experiment, however, the pattern of results, once again, did not mirror the predictions. The major problems for the model are clearly demonstrated by comparing the data to the predictions from the simulations shown in Figure 2.

The first prediction was that low-N and high-N word targets should always derive a greater benefit from the presentation of an unambiguous prime than should hermit word targets. The results of Experiment 2B are completely inconsistent with this prediction. Hermit word targets received far greater benefit from the presentation of an unambiguous prime (51 ms) than either the low-N or high-N word targets (29 ms and 28 ms, respectively).

The second prediction was that the amount of priming obtained for both hermit and high-N word targets should remain relatively constant as the word/nonword discrimination difficulty increases while the priming effect should increase for low-N word targets. Although this prediction was supported for the high-N word targets (there was only a 1 ms increase in the size of the priming effect as the word/nonword discrimination difficulty increased), the predictions appear to be wrong for both the low-N and hermit word targets. For the hermit word targets, as opposed to remaining relatively constant, the priming from unambiguous primes increased from 24 ms to 51 ms. For the low-N word targets, as the word/nonword discrimination difficulty increased, the amount of priming remained the same (29 ms) rather than showing the predicted increase.

The failure of both predictions casts doubt on the ability of the model to predict priming effects from unambiguous partial-word primes. Of all the results, the most troubling is that, contrary to predictions, hermit word targets received the most benefit from the presentation of an unambiguous prime when the word/nonword discrimination difficulty was high.

GENERAL DISCUSSION

Two main experiments were reported in this paper. In Experiment 1 ambiguous partial-word primes preceded low-N and high-N word targets when the word/nonword discrimination was easy (Experiment 1A) or difficult (Experiment 1B). Experiment 2 was similar except that unambiguous partial-word primes were used in place of ambiguous partial-word primes and hermit words were added to the target set.

The results of Experiment 1 were broadly supportive of the predictions made by Davis and Lupker's (2006) version of the IA model (McClelland & Rumelhart, 1981) (see Figure 1). The first of these predictions was that low-N word targets should derive a greater benefit from the presentation of an ambiguous prime than high-N word targets. In accord with this prediction, the results of Experiment 1 showed greater priming for low-N word targets than for high-N word targets, irrespective of the difficulty of the word/nonword discrimination; the difference was 19 ms when the discrimination was easy and 10 ms when it was more difficult.

A second prediction made by the model was that the size of the priming effect should decrease as the word/nonword discrimination becomes more difficult. This prediction was also supported by the data from Experiment 1. The priming effects for both low-N and high-N word targets were greater when the word/nonword discrimination was easy than when it was more difficult. As previously mentioned, this prediction and result is somewhat counter-intuitive, as effect sizes typically increase (or remain constant) when more difficult nonwords are used (although see Forster & Veres, 1998).

A third prediction made by the model was that the difference in the size of the priming effect between low-N and high-N word targets should increase as the word/nonword discrimination difficulty increases. This prediction was not supported. Increasing the difficulty of the word/nonword discrimination actually decreased the difference in the size of the priming effects from 19 ms to 10 ms. Thus, the predictions made by the model concerning ambiguous partial-word primes were essentially, but not fully, supported.

The results of Experiment 2 were less supportive of the model's predictions. Before considering the model's predictive failures here, we first discuss some successful predictions made by the model with respect to the data reported in Experiment 2. The first of these concerns the ambiguity effect previously reported by Hinton et al. (1998), whereby priming effects are larger for unambiguous than for ambiguous primes. Using Hinton et al.'s experimental stimuli, Davis (2003) showed that the IA model correctly predicts this pattern due to the fact that ambiguous primes (unlike unambiguous primes) pre-activate competitors of the target, and the resulting inhibition reduces the facilitatory component of priming. Exactly the same ambiguity effect was observed in the present experiments. In the experiments with difficult nonwords (Experiments 1B and 2B), the priming effects for the low-N and high-N targets were 17 ms larger when preceded by unambiguous primes than when they were preceded by ambiguous primes. With a relatively high M criterion (of .71, to simulate a difficult word/nonword discrimination), the IA model implemented here predicted a difference, in the same direction, of 23 cycles. In the experiments with easy nonwords (Experiments 1A and 2A), there was a smaller ambiguity effect. Priming effects for the low-N and high-N targets were 9 ms larger when preceded by unambiguous primes than when they were preceded by ambiguous primes. With a relatively low M criterion (of .59, to simulate an easier word/nonword discrimination), the IA model implemented here predicted a difference, in the same direction, of 11 cycles. Thus, the model correctly predicts both the ambiguity effect and the finding that this effect is greater when the word/nonword discrimination is more difficult.

Another prediction of the model that was successfully verified in Experiment 2 was the finding of robust priming effects for high-N word targets when unambiguous partial-word primes were used. This finding is interesting because it appears to violate the neighbourhood density constraint that is typically observed in masked form priming (Davis & Lupker, 2006; Forster et al., 1987). Specifically, word targets that belong to low density neighbourhoods (i.e., words that have few neighbours) show noticeable priming effects, whereas the priming effects for word targets from high density neighbourhoods (i.e., words that have many neighbours) are usually either small or nonexistent. However, the robust priming effects that we observed for high-N word targets when unambiguous partial-word primes were used (see Tables 3 and 4) indicate that the typically observed density constraint does not always hold.

This result is exactly as predicted by the IA model. Unambiguous partial-word primes, by virtue of the fact that they are unambiguous, belong to a low-density neighbourhood regardless of the target N (i.e., cr#wn only resembles the target CROWN). Thus, the presentation of an unambiguous partial-word prime will provide little, if any, activation to competitors of the target (e.g., shared neighbours – van Heuven et al., 2001) while at the same time giving all types of targets a similar 'head start' in processing.

An interesting prediction follows from the present findings. According to the IA model, unambiguous form primes should operate in the same way as unambiguous partial-word primes. That is, high-N word targets may show substantial priming (i.e., the density constraint may not hold) if the form primes have no neighbours except for the target (i.e., the partial-word prime cr#wn replaced by the nonword prime crawn). This possibility merits future investigation (cf. van Heuven et al., 2001).

Predictive failures of the modified IA model

Although the modified IA model had a number of predictive successes, the results of Experiment 2 provided evidence contradicting two of the predictions of the model (see Figure 2). The first prediction that was not supported was that low-N and high-N word targets should always derive a greater benefit from the presentation of an unambiguous prime than hermit word targets. When the word/nonword discrimination was easy, low-N and high-N word targets received (numerically) slightly greater amounts of priming (29 ms and 27 ms, respectively) than hermit word targets (24 ms). However, when more difficult nonwords were used, hermit word targets showed a much larger priming effect (51 ms) than either low-N or high-N word targets (29 and 28 ms, respectively).

The second unsupported prediction concerned the changes in the amount of priming for the three word types as a function of the difficulty of the word/nonword discrimination. The model predicted that the amount of priming for low-N word targets should increase as the difficulty of the word/nonword discrimination increases, whereas the amount of priming for both hermit and high-N word targets should remain relatively constant. Although high-N word targets showed the predicted pattern, the other two target types did not. The size of the priming effect for hermit word targets increased from 24 ms to 51 ms, whereas the size of the priming effect for low-N word targets remained constant at 29 ms.

The discrepancy between the obtained results and the predictions suggest that Davis and Lupker's (2006) implementation of the IA model does not adequately capture human performance in these experiments. The question thus arises as to whether altering some of the model's assumptions might allow it to better account for the obtained results.

Modifications to the model that could help explain the data

SOLAR's node bias. Although no mention of it was made in the prior discussion because that discussion focused on the sizes of priming effects, the IA model incorrectly predicts that hermit targets should be responded to more rapidly than targets with neighbours. The data, in contrast, went in the opposite direction, with hermits being 50 ms slower than words with neighbours in Experiment 2A, and 40 ms slower in Experiment 2B.

It is possible that the slower latencies for the hermits than for words with neighbours at least partially reflect difficulties with stimulus matching. Although the three target conditions were matched with respect to Kucera and Francis (1967) word frequency, the match was not as good for the CELEX frequency count: log CELEX frequency was significantly smaller for the hermits than for the non-hermits ($p < .05$ in a two-tailed test). Likewise, age-of-acquisition (AoA) was not well-matched for hermits versus non-hermits. AoA estimates were obtained from the combined Bristol/MRC database (Stadthagen-Gonzalez & Davis, 2006) for 79 of the 90 word targets. A two-tailed test showed that hermit words were, on average, later-acquired than non-hermits ($p = .02$). This difference is likely to have contributed to the observed difference in RTs, given the accumulated evidence for the importance of AoA in visual word identification (see Juhasz, 2005, for a review).

Even if one can explain part of the latency difference between hermits and non-hermits in terms of these stimulus matching issues, however, it seems unlikely that resolving these issues would allow the IA model to fully explain why hermits were substantially slower than non-hermits. The reason is that the IA model relies on differences in resting activity levels to encode differences in word frequency and, within the model, resting activity levels only have much of an impact on word identification latency to the extent that they influence the competition between different word nodes. Thus, even if hermit words were assigned considerably lower resting activity levels than non-hermits (to reflect their lower frequency of occurrence and later AoA), they would still enjoy an advantage over non-hermits, because they have no close competitors to inhibit the rapid growth of their activation.

The SOLAR model (Davis, 1999) appears to provide at least a partial solution to not only this problem but also the problem of explaining why the hermit targets provided the largest amount of priming in Experiment 2B. SOLAR assumes a similar lateral inhibitory mechanism to the IA model, but uses a different mechanism to encode word frequency. In SOLAR, each word node has an associated property called a node bias which controls both the maximum activity of the node and (because of the model's shunting activity equations) the rate at which node activity grows for a fixed input. Words of higher frequency or earlier age of acquisition (AoA) are associated with larger node biases, and therefore are activated more rapidly than low frequency/late-AoA words. This aspect of the model would allow it to predict longer latencies for words with smaller node biases (i.e., the hermits). In addition, with hermits now showing longer latencies, there would be more room for masked primes to facilitate their processing. Hence, this account could explain why partial-word priming effects tend to be larger for hermits than for non-hermits.

Redefining the neighbourhood. Another factor that may have an important bearing on the ability of the IA model to explain the present results concerns the definition of orthographic neighbours. Note that the predictions for all the models were derived from the assumption that when a word is presented, it only provides activation to the correct word node and to incorrect word nodes which differ from the presented word at only one letter position (i.e., Coltheart et al.'s, 1977, definition of a neighbour). Thus, a prime like *sa#ce* should activate the lexical representation for the target *SAUCE*, but not the representation for the word *SPACE*. This strict definition of a neighbour may be unrealistic and may have something to do with the failure of the modified IA model.

Recent empirical results have indicated that Coltheart et al.'s (1977) original definition of a word's neighbourhood is too narrow. For instance, Bowers, Davis, and Hanley (2005) showed that words that contain other words that belong to a particular semantic category (e.g., *hatch* contains *hat* which is a member of the 'clothing' category) or words that are contained in longer words that belong to a particular semantic category (e.g., *bee* is contained in *beer* which is a member of the 'drinks' category) take longer to categorise in a semantic categorisation task involving those categories. In addition, Davis and Taft (2005) reported that nonwords created by adding a letter to the beginning of a word (e.g., *smade*) were harder to reject than control nonwords (e.g., *smoad*). Similarly, Van Assche and Grainger (2006) reported that primes created by inserting extra letters (e.g., *jusstice-JUSTICE*) provided essentially the same amount of priming as repetition primes (e.g., *justice-JUSTICE*) even when the inserted letter is different from all the other letters in the prime (e.g., *juastice-JUSTICE*). There is also evidence that nonword primes that are created by transposing two adjacent letters (e.g., *jugde-JUDGE*) (Andrews, 1996; Perea & Lupker, 2003a, 2003b) or two non-adjacent letters (e.g., *caniso-CASINO*) (Perea & Lupker, 2004) facilitate target processing in masked priming experiments.

According to Coltheart et al.'s (1977) definition of a word's neighbourhood, words like *hatch* and *hat* or *bee* and *beer* are not neighbours of each other (nor is a nonword like *juastice* a neighbour of *justice* or *jugde* a neighbour of *judge*). Thus, the current forms of most lexical retrieval models assume that the presentation of one of these words (or nonwords) will, at most, minimally activate the lexical representation of the relevant word. Suppose, however, that the definition of a word's neighbourhood were expanded to include words formed by letter additions, deletions, and transpositions. In the present experiments, the hermit word targets had zero neighbours, the low-N word targets had a mean of 1.5 neighbours, and the high-N word targets had a mean of 6.2 neighbours using Coltheart et al.'s definition of a word's neighbourhood. However, using the expanded definition of a word's neighbourhood, the number of neighbours for each condition increases. The hermit word targets would have a mean of 1.9 neighbours, the low-N word targets would have a mean of 4.0 neighbours, and the high-N word targets would have a mean of 8.7 neighbours. This expanded definition of a word's neighbourhood, if implemented in Davis and Lupker's (2006) version of the IA model, would, therefore, change the predictions for the sizes of the priming effects.

In order to obtain precise predictions concerning what would occur if the model were to implement this new definition of a word's neighbourhood, the input coding scheme in the IA model would need to be altered and the simulations would have to be run again. In particular, this new letter coding scheme would need to cause, for example, the letters for *cat* to activate the lexical unit for the word *CAST*. In the absence of such a model, however, general predictions concerning what results the simulation would produce can be made.

With respect to the ambiguous prime experiments (see Figure 1), the general prediction appears to be that as target neighbourhood size increases, the size of the priming effect decreases. Since the neighbourhood sizes would now be greater for both the low-N (4.0 versus 1.5) and the high-N (8.7 versus 6.2) word targets, the prediction would be that the priming effects should merely be smaller than what was originally predicted for both word conditions. These predictions are reasonably consistent with the observed results. However, the model still might not be able to explain why the obtained difference in the size of the priming effect was greater when the word/nonword discrimination was easy as opposed to when it was more difficult.

Concerning the unambiguous prime experiments (see Figure 2), the original prediction was that low-N and high-N word targets should always receive a greater benefit from the presentation of the prime than the hermit word targets. The prediction for small priming effects for hermit targets is predicated on the assumption that the targets used here actually are hermits. However, based on the new definition of a word's neighbourhood, only three of the 30 word targets are hermits and the average number of neighbours for the hermit word targets is actually 1.9. Thus, the priming effect pattern for the hermit word targets should be similar to what was predicted for the low-N word targets in Figure 2. In fact, consistent with this prediction, the size of the priming effect for the hermit word targets did increase as the word/nonword discrimination difficulty increased (from 24 ms to 51 ms).

Since the neighbourhood size for the low-N word targets would also increase by using this new definition, the predicted priming effect pattern for the low-N word targets should be similar to that of the high-N word targets in Figure 2 (i.e., the size of the priming effect should remain relatively constant as the word/nonword discrimination difficulty increases). That is also what occurred. The size of the priming effect was 29 ms with both easy and hard nonwords. Note also that the priming effect for high-N word targets also remained essentially unchanged as the word/nonword discrimination difficulty increased as would also be predicted. What needs to be pointed out, however, is that with neighbourhoods defined in this new way, primes that are presently defined as unambiguous may become ambiguous.[5] Thus, using the patterns displayed in Figure 2 in order to derive predictions here may be somewhat misleading.

It would appear, therefore, that the failure of Davis and Lupker's (2006) version of the IA model to account for the data may be, at least partly, due to an inadequate definition of what a word's neighbour is. If the definition were expanded to include addition, deletion, and transposition neighbours then the model would appear to be better able to account for the obtained data, at least for the unambiguous primes.

Conclusion

Although Davis and Lupker's (2006) version of the IA model can make fairly accurate predictions concerning priming effects with ambiguous primes, the

[5] We thank Marc Brysbaert for pointing this out to us.

model fails to explain some aspects of the priming results with unambiguous primes, particularly with respect to hermit word targets. The results of these experiments suggest that the current assumptions about what constitutes a word's neighbourhood need to be altered. An additional improvement to the IA model could also come about by implementing SOLAR's assumptions about the impact of frequency and AoA on lexical representations.

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APPENDIX
WORD AND NONWORD LISTS

Hermit (N = 0) Word targets with their unambiguous primes
CIGAR, #igar, ELBOW, el#ow, CLIFF, cl#ff, ARROW, arr#w, OPIUM, #pium, IVORY, ivo#y, ESSAY, essa#, CABIN, cabi#, WIDOW, w#dow, RANCH, ranc#, MOVIE, #ovie, OCEAN, o#ean, SUGAR, s#gar, PIANO, pian#, GUARD, #uard, WHEEL, whee#, UNCLE, u#cle, RIFLE, rifl#, KNIFE, k#ife, RABBI, ra#bi, SALAD, sal#d, EAGLE, e#gle, AISLE, #isle, RELIC, rel#c, MAPLE, mapl#, ALGAE, al#ae, ULCER, ul#er, JEWEL, #ewel, OUNCE, ounc#, CRUMB, #rumb

Low-N (N = 1 to 2) Word targets with their unambiguous and ambiguous primes
MOTOR, mot#r, #otor, LEMON, lemo#, #emon, SAUCE, sa#ce, sauc#, TOOTH, toot#, #ooth, GIANT, gi#nt, g#ant, QUEEN, q#een quee#, RIDGE, ridg#, #idge, THUMB, t#umb, thum#, JUICE, ju#ce, juic#, GLOBE, g#obe, glo#e, ONION, onio#, #nion, TROOP, troo#, #roop, SPRAY, #pray, s#ray, FLEET, fl#et, #leet, NURSE, nurs#, #urse, LODGE, lodg#, l#dge, FLOOD, fl#od, floo#, LOBBY, lobb#, #obby, PENNY, p#nny, pe#ny, CLOUD, #loud, clou#, FENCE, fen#e, #ence, MAYOR, #ayor, ma#or, GUEST, g#est, gues#, CLOTH, c#oth, clot#, CROWD, #rowd, crow#, SMILE, #mile, smi#e, TUNIC, tun#c, t#nic, CRYPT, #rypt, cr#pt, SNAIL, #nail, sna#l, TRASH, tra#h, #rash

High-N (N = 5–8) Word targets with their unambiguous and ambiguous primes
BEACH, beac#, #each, MOUSE, m#use, mo#se, COUCH, couc#, co#ch, SHEEP, #heep, s#eep, LUNCH, lunc#, #unch, PAINT, pai#t, p#int, TRACK, t#ack, tr#ck, BREAD, b#ead, brea#, FERRY, ferr#, #erry, PATCH, pa#ch, p#tch, TOWER, tow#r, towe#, CANDY, cand#, #andy, CROWN, cr#wn, #rown, BELLY, be#ly, b#lly, LEVER, lev#r, l#ver, WOUND, w#und, wou#d, CLOCK, cloc#, clo#k, STOVE, #tove, sto#e, GROVE, grov#, g#ove, PASTE, pa#te, past#, TRAIL, t#ail, trai#, BENCH, #ench, be#ch, SHEET, #heet, shee#, BRAIN, br#in, brai#, PURSE, p#rse, #urse, BRICK, bric#, #rick, SHELL, #hell, shel#, STAIN, #tain, stai#, POUCH, pou#h, po#ch, SPIKE, #pike, spi#e

Hermit (N = 0) Nonword targets
VENER, PLICH, NAIPT, GRULP,PEWOR, APPIT, THRAG, YOWND, HALST, TREDA, ZOURK, KREMP, TAMAL, RODIS, SKORP, LORIT, NATEM, OPUNA, ORTIN, INOMY, LORAN, RUXOT, ALGOM, LAISO, SHURD, ADIUM, HIEFS, FEGEL, POSOR, GEIVY,

YOLER, OLVAN, EICLE, MOOLI, AUNEY, LODEM, KAPIE, LEPTO, MIEGY, BOSUC, NAURO, NOGAL, RAMIN, MARIL, BROIT, DOREL, PONIL, OBBEL, CIMOL, WRALN, CINAM, DIRDA, FOIDE, AVALO, LAUMO, GONIL, TARBO, UDIAM, MUNIE, URGYM, SHOYD, TIRON, POSON, BENUR, PIRAL, BOSAC, FOPOR, TROAM, MACKO

Low-N ($N = 1$ to 2) Nonword targets
EMPLE, KELSH, ROOZE, BENIM, GLEEK, GIFLE, GLEST, FRENT, REASY, BLATT, ORGYN PLUST, BRICH, TRENO, TIDAM, THONS, SCOND, GORCH, SLOAT, PROTH FALET, GAPLE, BIOKE, ALODE, CLEED, DAOLY, FERCH, DROST, CHEAB, CHORK, GRIRE, GRIPA, BLIPE, KIRDA, DOVIS, COLIT, PLOSK, EBBEL

High-N ($N = 5$–8) Nonword targets
PLAVE, FLUCK TREAM, DRICK, BRAPE, ROVEN, LEATH, DRIGS, PLICK, SOUCH, HEAST, STAIP, SLOTE, TRACH, JASTE, ARONE, FURES, POLER, MOUGH, SHOON, TRIME, LITCH, SHOOP, BURKS, PLARE, PROWN, CRAME, BLASS, GRESS, CREET