Journal of Experimental Psychology:
Learning, Memory, and Cognition
2000, Vol. 26, No. 4, 945–972

0278-7393/00/$5.00 DOI: 10.1037//0278-7393.26.4.945

Repetition Priming of Words, Pseudowords, and Nonwords

Craig E. L. Stark
Carnegie Mellon University

James L. McClelland
Carnegie Mellon University and
Center for the Neural Basis of Cognition

In 5 experiments, the authors assessed repetition priming for words, pseudowords, and nonwords using a task that combines an implicit perceptual fluency measure and a recognition memory assessment for each list item. Words and pseudowords generated a consistently strong repetition effect even when there was a failure to recognize the stimulus. In 2 of the experiments, the repetition effect for nonwords was reliably above chance even when there was a failure to recognize the stimulus. The authors propose a parallel distributed processing (PDP) model based on the work of J. McClelland and D. Rumelhart (1985) as a way to understand the mechanisms potentially responsible for the pattern of findings. Although the error-driven nature of learning in the model results in a poor fit to the nonword priming data, this is not endemic to all PDP models. Using a model based on Hebbian learning, the authors instantiate a property that they believe is characteristic of implicit memory—that learning is primarily based on the strengthening of connections between units that become active during the processing of a stimulus. This model provides a far more satisfactory account of the data than does the error-driven model.

In the traditional implicit memory paradigm, participants are exposed to a set of stimuli (such as a list of words) and later given a task to perform on these items that requires no explicit reference to the initial exposure. Performance on typical tasks such as the perceptual identification task (e.g., Feustel, Shiffrin, & Salasoo, 1983; Jacoby & Dallas, 1981) and the word-stem or fragment completion task (e.g., Graf, Mandler, & Haden, 1982) is often enhanced for previously exposed items relative to unexposed items. This phenomenon is known as the *repetition priming effect*.

Repetition priming has been dissociated from recognition memory in both normal experimental participants (e.g., Jacoby, 1991; Jacoby & Dallas, 1981; Schacter, 1992; Tulving, Schacter, & Stark, 1982) and amnesic patients (e.g., Cermak, Talbot, Chandler, & Wolbarst, 1985; N. Cohen & Squire, 1980; Hamann & Squire, 1997a; Stark & Squire, in press). This dissociation, along with dissociations between recognition memory (or recall) and other tasks such as skill learning (N. Cohen & Squire, 1980; Corkin, 1968; Milner, 1962) and category learning (Squire & Knowlton, 1995), has led many researchers to propose the existence of implicit learning systems capable of reflecting prior experience without explicit awareness (Anderson, 1993; Eichenbaum, 1992; McClelland, McNaughton, & O'Reilly, 1995; Squire, 1992; Tulving, 1987; Weiskrantz, 1990).

In the present research, we collected data on the amount of repetition priming that occurs for stimuli that vary in their degree of novelty (i.e., consistency with participants' prior knowledge). We believe that such data will inform and constrain our understanding of the mechanisms governing implicit memory. Consider, for example, the well-documented phenomenon of priming familiar information (e.g., words or pictures of familiar objects). This phenomenon has been accounted for by a range of theoretical mechanisms. One such mechanism involves residual influences on "logogens" (Morton, 1969) or similar preexisting representations of the stimuli (e.g., Diamond & Rozin, 1984; Graf & Mandler, 1984; Wickelgren, 1979). In contrast, other researchers have suggested that priming is the result of the formation of new, often perceptually based, memory representations that maintain recently processed information (e.g., Bowers & Schacter, 1993; Marsolek, Kosslyn, & Squire, 1992; Schacter, 1992; Schacter, Cooper, & Delaney, 1990).

Although both mechanisms are consistent with priming of words and other familiar information, these two mechanisms differ in their predictions for priming of novel information. If activation and strengthening of logogens is the source of priming, then a logogen tuned to detect that information (or very similar information) must exist for priming of that information to occur. Conversely, if priming is the result of the formation of new, potentially perceptually based memories, then priming should be a function of whether or not a new memory can be formed, or whether, as Schacter et al. (1990) suggested, stimuli can gain access to the processing systems within which such memories are formed. It should be noted that this is not meant to represent an exhaustive list of potential mechanisms of priming (indeed, in this article we

Craig E. L. Stark, Department of Psychology, Carnegie Mellon University; James L. McClelland, Department of Psychology, Carnegie Mellon University and Center for the Neural Basis of Cognition, Pittsburgh, Pennsylvania.

Craig E. L. Stark is now at the Department of Psychiatry, University of California, San Diego.

The experiments and simulations presented here were part of Craig E. L. Stark's doctoral dissertation. We thank John Anderson, Lynne Reder, Dave Plaut, Jon Cohen, Marlene Behrmann, Randy O'Reilly, and Chad Dawson for their assistance.

Correspondence concerning this article should be addressed to Craig E. L. Stark, Veterans Affairs Medical Center, 116A, 3350 La Jolla Village Drive, San Diego, California 92161. Electronic mail may be sent to cstark@ucsd.edu.

Table 1
Summary of Experimental Conditions

Experiment	*n*	Stimuli	No. of items for each type (study/test)	Study task	Test task	Pseudowords	Nonwords
1	27	W, P, N	40/40	CID	2-choice CID-R	Swap onset and coda of words	Random 4 of {*k, g, d, p, b, z, f, x, q, j, g*}
2	24	P, N	60/120	CID	4-choice CID-R	Swap onset and coda of words	Replace pseudoword's vowels and swap 3-4-1-2
3	52 (26 + 26)	W, P, N	30/60	CID or rating	4-choice CID-R	Swap onset and coda of words	Replace word's vowels and swap 3-1-4-2
4	60 (30 + 30)	W, N	39/78	CID	4-choice CID-R or CID		Replace word's vowels and *s* or *t* and swap 3-1-4-2
5	60 (30 + 30)	W, P	50/100	CID	4-choice CID-R or CID	Swap onset and coda of words	

Note. W = words; P = pseudowords; N = nonwords; CID = continuous identification; CID-R = continuous identification with recognition.

present an alternative mechanism based on connectionist principles). Rather, these two mechanisms are presented both as being representative of current hypotheses and as demonstrations of the theoretical informativeness of priming for multiple kinds of information.

In regard to these hypotheses, there is currently some evidence that appears to favor the latter mechanism, often referred to as the *acquisition model* of implicit memory. Repetition priming has been found for novel possible but not impossible three-dimensional drawings (e.g., Schacter et al., 1990) and novel letter strings in the form of pseudowords (e.g., Bowers, 1994; Feustel et al., 1983; Rueckl, 1990; Rueckl & Olds, 1993; Salasoo, Shiffrin, & Feustel, 1985; Whitlow & Cebollero, 1989). Although informative, these data do not compellingly endorse the acquisition model nor refute the logogen or *modification model.* Ratcliff and McKoon (1995) have accounted for the absence of priming of impossible objects by assuming a combination of an overall bias to respond "possible" to familiar stimuli and a contamination of the priming data from explicit recollection of the object. Together, these factors produce facilitation for possible but not impossible objects. With respect to pseudoword priming, although pseudowords are novel in that as an entity they have probably never been seen by experimental participants (and thus have no logogen tuned for the string as a whole), they are similar to familiar words and are composed of portions of such words. By proposing either the partial activation of orthographically similar words or the activation of logogens tuned to subword orthographic patterns, the logogen modification hypothesis can be made consistent with pseudoword priming.

In this article, we present data from five experiments (see Table 1 for an overview) that empirically address three questions that will help inform and constrain our understanding of the mechanisms responsible for repetition priming. The first is whether there is a repetition priming effect for nonwords designed to be as dissimilar to words as possible. The review we present below shows that although several studies have demonstrated a priming effect using nonword stimuli (Bowers, 1994; Dorfman, 1994; Hamann & Squire, 1997b), they are all open to several ways in which nonword priming could have been contaminated and enhanced. Here, we present an additional source of evidence that even highly nonwordlike nonwords can show a repetition priming effect. A second related question is the relative magnitude of priming effects for words, pseudowords, and nonwords. We demonstrate that nonwords show a smaller priming effect than words or pseudowords and that pseudowords can show an even larger effect than words.

Finally, we address the issue of whether explicit recollection of prior occurrence of the stimuli could be the source of any priming effects found by presenting an alternate methodology to those already in use (e.g., demonstrations of failure to find level of processing effects on priming, demonstrations of normal priming in amnesic populations, application of the process dissociation procedure, etc.). We use a task first developed by Feustel et al. (1983) in which a perceptual fluency measure is combined with a forced-choice recognition memory measure on each trial. We extend Feustel et al.'s work by examining priming for items that the participant failed to recognize at the time the fluency measurement was taken. Using this task, which we call continuous identification with recognition (CID-R), we demonstrate that even when participants fail to recognize items, there is still a repetition priming effect for words, pseudowords, and nonwords. In Experiments 4 and 5, we also demonstrate that the inclusion of the recognition memory judgment does not qualitatively change the pattern of results.

After presenting these data, we explore a computational account of repetition priming within a connectionist modeling framework. We begin with an existing model of priming (McClelland & Rumelhart, 1985) and show how and why it can demonstrate several of the central empirical findings. However, we show that it provides a particularly poor fit to the nonword priming data. We propose that this lack of fit is the result of using an error-correcting algorithm (one that changes the weights according to the difference between the network's current behavior and ideal behavior) as the basis for learning. Within the McClelland and Rumelhart model, the use of an error-correcting learning rule tends to result in the greatest priming for nonwords. The reason is that the model processes these items poorly, leaving a great deal of error to be corrected. The larger the error, the greater the changes in the weights, and the greater the resulting impact on performance. Thus, the finding that nonwords show the least priming appears to be at odds with the error-correcting approach. We go on to show that the findings are consistent with a Hebbian approach to learning in which the size of the weight changes is proportional to the product of the activation-connected units. In this case, nonwords produce relatively small activations because they are not consistent with the lexical knowledge already known to the network, so they produce small weight changes and, therefore, small priming effects. Thus, we demonstrate that an alternate method of training, one that is based on the coactivation of units rather than an error signal (the Hebb rule; Hebb, 1949), results in a far superior fit to the data. As explained in the General Discussion of the Simulations, this model captures what may be an important aspect of implicit learning, which may help account for several aspects of the pattern of successes and failures seen in studies of learning in amnesia.

In the remainder of this introduction, we review the evidence for priming novel information, discuss Feustel et al.'s (1983) methodology, and show how we have elaborated on it to determine whether explicit recollection of the stimulus during testing could be the source of any repetition priming effect found.

Repetition Priming of Novel Information

In examining the literature concerning priming of novel information, we focus attention on repetition priming of letter strings. We chose to focus on letter strings not only because of their widespread use in the implicit memory literature but also because of the relative ease with which one can manipulate similarity of novel letter strings to existing words. For example, although *mave* and *pdxq* are both novel letter strings, *mave* is clearly the more wordlike of the two.

As noted, although the demonstration of pseudoword priming is informative, it does not fully address the issue of priming novel information. To address this issue, we must use letter strings that are as nonwordlike as possible so that preexisting knowledge related to words can be eliminated as a source of any repetition priming effect found. Although all letter strings will share some properties with words (e.g., like words, they are a series of letters), we can construct stimuli so that they share as few properties with words as possible. Specifically, we can construct letter strings that are exceptionally difficult to pronounce, that are composed of highly unfamiliar subword units (e.g., letter pairs and triples), and that result in a very poor partial match to words. We call such stimuli nonwords.

Very little research has been conducted on repetition priming of nonwords or even less rigidly defined nonwordlike letter strings. Dorfman (1994) reported small amounts of repetition priming in a lexicality-rating task for multisyllabic letter strings whose syllables are not found in the English language (e.g., *erktofe*). Although such stimuli may be less wordlike than some pseudowords, these stimuli are still somewhat wordlike. They are pronounceable and can be formed from segments of English words. For example, *erktofe* can be formed from portions of *perk, toe,* and *fed.*

In another study, Bowers (1994) examined priming for words, pseudowords, and random letter strings by using a *t*-scope identification task. Although Bowers found a significant priming effect for all three stimulus types, a list of uncontrolled random letter strings may contain some items similar enough in structure to words to leave the issue of priming novel letter strings unsettled. For example, although the strings *blck, brmp,* and *tnxj* are all consonant strings that could be generated at random, their concordance with English structure is potentially quite different. In contrast to *tnxj,* both *blck* and *brmp* are fairly pronounceable despite the lack of vowels. Processing either of these might be similar to processing pseudowords like *brop.* Further, if asked to pronounce "blck" one is likely to generate *blak, blok,* or *blek,* resulting in a homophone of an English word (or common slang in the case of *blek*).

In addition, the relative priming effect sizes for the three stimulus types are unclear from the Bowers (1994) data. Specifically, his results do not address the question of whether the amount of priming for the random letter strings is comparable to the amount of priming for words or pseudowords. In Experiment 3 (where random letter strings were used), repeated pseudowords produced a consistent 16% increase in the probability of correct *t*-scope identification regardless of study task. Random letter strings, however, produced numerically smaller 7% and 13% priming effects, dependent on the study task used. Unfortunately, Bowers did not report whether the differences in effect sizes between pseudowords and random letter strings were significant.

Finally, in a study done in parallel with this research, Hamann and Squire (1997b) examined priming of words, pseudowords, and nonwords in normal and amnesic patients. Using *t*-scope identification, they found significant priming for all three stimulus types and significant differences among them with words showing the largest priming effect followed by pseudowords and nonwords. Amnesic and normal participants showed similar priming effects across all three stimulus types.

These results are also not fully able to address the questions posed here. Despite Hamann and Squire's (1997b) attempts to equate baseline identification accuracy across stimulus types, the baselines differed significantly. Words were identified more accurately than pseudowords, and pseudowords were identified more accurately than nonwords. This raises the possibility that the numerically largest priming for words and the smallest priming for nonwords simply reflect a percentage change in a numerically larger baseline probability of identification for words and numerically smaller baseline probability for nonwords. Therefore, from these data, we cannot determine the relative effect sizes.

In their effort to address the issue of whether the priming found for nonwords might be the result of priming similar words, Hamann and Squire (1997b) examined the correlation between the priming effect on a nonword and the summed lexical frequency of its bigrams (both position dependent and independent) and found no correlation. Although such a null result is consistent with a lack of contribution to priming from similar words or subword elements, it would be far better to control for this possibility by using nonwords that are as nonwordlike as feasible. Finally, although impaired in their recognition memory, the amnesic patients' recognition memory accuracy was not at chance, thus making it possible for recognition memory to have enhanced priming (see Recognition Memory and Priming below).

From the existing data, we can conclude that a significant repetition priming effect exists for words and for pseudowords but has not been definitively shown to exist for maximally nonwordlike nonwords, and the relative magnitudes of priming for these different types are unclear. In the experiments presented in this article, we examine repetition priming in a perceptual fluency task by using words, pseudowords, and nonwords. We show that repetition priming exists for these nonwords but that the effect is smaller in magnitude than the effect found for words and pseudowords.

Recognition Memory and Priming

Until this point, we have largely ignored the potential relationship between explicit recollection and the facilitation found in repetition priming tasks. Although we adopt the view that repetition priming can occur in the absence of explicit recollection (e.g., N. Cohen & Squire, 1980; Schacter, 1990; Squire & Zola-Morgan, 1988; Tulving et al., 1982), it is always possible that explicit recollection of the stimulus influences performance on some trials (see Tenpenny, 1995, for review). A number of methods for exploring the relation between recognition memory and priming have been proposed, including (a) the use of amnesic patients (e.g., Graf & Schacter, 1985; Shimamura & Squire, 1984; Hamann & Squire, 1997a,b; Stark & Square, in press), (b) tests for stochastic independence between priming and explicit memory (Jacoby & Witherspoon, 1982; Light, Singh, & Crapps, 1984; Schacter, Harbluk, & McLachlan, 1984; Tulving, 1985; Tulving et al., 1982), (c) tests for an effect of level of processing during study on priming (Bowers, 1994; Jacoby & Dallas, 1981; Roediger & McDermott, 1993), (d) the method of triangulation (Hayman & Tulving, 1989), and (e) the process dissociation procedure (e.g., Jacoby, 1991). Although each method has merit, none is without difficulty. For example, almost all amnesic patients available for study are impaired in their recognition memory but not at chance. It is difficult to disprove the hypothesis that a repetition priming effect is the result of this residual ability (but see Hamann & Squire, 1997a, and Stark & Squire, in press, for an exceptional case). In the case of tests for stochastic independence, the method designs are such that any dependence between recognition memory and priming can be decreased enough that the results would support a claim of independence (Shimamura, 1985). In each of the studies that report a finding of independence, the recognition memory test precedes the priming task. As Shimamura demonstrated, if exposure to the stimuli during the recognition memory test produces a priming effect in addition to the one caused by the initial exposure, then this "test priming" can significantly weaken any preexisting dependence. Alternatively, if a typical priming task such as *t*-scope identification or fragment completion precedes the recognition memory test, then dependence can be induced on the basis of the probabilistic nature of the priming task. Items successfully identified or completed by the participants are given an additional exposure on which recognition is performed, thereby weakening any test for independence.

In this article, we use a task first developed by Feustel et al. (1983) in an attempt to determine directly whether repetition priming exists for items that are not explicitly recognized. In the CID-R task, recognition memory for each item is assessed immediately following a perceptual fluency measurement of that item. If the participant does not recognize the item as being repeated (i.e., responds "new") when asked immediately after identifying the item, we take this as evidence that explicit recollection did not occur and any repetition effect found is not due to explicit recollection. Although those items the participant recognizes as "old" may or may not have distorted the reaction time (RT) during identification as a result of explicit recollection, this is not the case when the participant responds "new." For these trials, we may not have obtained an accurate assessment of the true magnitude of the priming effect. For example, we may have underestimated the magnitude of the priming effect as a result of any factors that led to both increased priming and increased recognition memory accuracy. However, we can be assured that any effect found did not result from explicit recollection.

The CID-R Task Methodology

Like most repetition priming experiments, the technique presented here is divided into a study phase and a test phase. Likewise, the study phase is disguised, and participants are asked to perform some sort of incidental encoding task on a list of stimuli (e.g., give liking judgments). After a distraction period, the testing phase begins. Unlike traditional implicit memory experiments, the technique involves the use of a test task in which an implicit measure (RT to identify a stimulus) and an explicit measure (recognition memory ability) are assessed in immediate succession on each trial. Note that this task is virtually identical to one of the tasks developed by Feustel et al. (1983) to explore repetition priming of words and pseudowords. The analysis method presented here, however, is substantially different. Whereas Feustel et al. focused on the "yes" recognition memory responses to determine whether items that are orthographically similar to study items have elevated false-alarm rates, we used the "no" recognition memory responses to determine whether priming exists for items that were not recognized.

In the CID-R task, participants are alternately presented with a letter string and a mask, with the duration of the letter string presentation increasing within each fixed-length cycle. In this way, as the trial progresses, the visual signal-to-noise ratio increases, and the stimulus appears to become clearer (see Figure 1). The participant's task is to identify the letter string by verbally naming the letters as soon as possible while maintaining accurate responses (items inaccurately identified at study or test are removed from the analysis). As soon as the response begins, the mask is presented, a voice key records the RT, and the flashing of the stimulus is halted. Participants are then given a recognition memory probe and asked whether they believe the stimulus they just

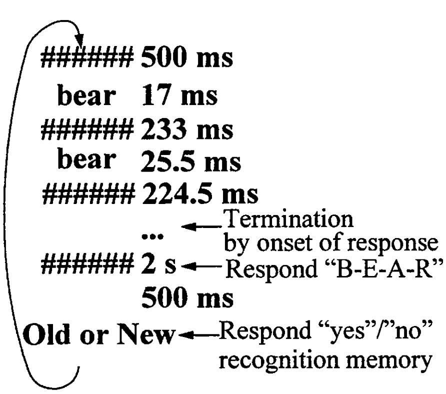

Figure 1. Design of a continuous identification with recognition trial. The letter string becomes increasingly clearer with time until the participant identifies the letter string by verbally naming the letters. After identifying the letter string, a yes–no recognition memory probe is given. In this way, for each item, we gather both a perceptual fluency measurement and an assessment of whether the participant can recognize the item as being old at the time of identification.

identified is one that was in the initial phase of the experiment or whether it is novel.

The important feature of this task is that for each item we gather both a perceptual fluency measurement and a measure of whether the participant can recognize the item as being "old" at the time of identification. Because all items in the task are accurately identified (unlike the traditional *t*-scope or fragment completion tasks), we severely limit the potential of artificially introducing between our two measures the sort of dependencies described by Shimamura (1985). Recognition memory cannot be selectively boosted as a result of identification of only some of the items as all participants accurately identify virtually all items.[1] Any effect on recognition memory performance by identifying the stimulus should be relatively constant across the primed and unprimed conditions. Further, by assessing the two measures simultaneously, we can address the question of whether explicit recollection of the stimulus could have been a factor in the time taken to identify the stimulus. We no longer need to rely on recognition memory performance at some later time, which may have decayed or improved on an item-by-item basis over the interval for which we know whether the participant could recognize the item at the time the priming assessment was made. If the participant believes the stimulus was not on the original list and responds "new," we assume explicit recollection of the item cannot have influenced the time required to identify the item. Although this methodology appears to invite the use of recognition memory during performance of the identification task, we demonstrate in Experiments 4 and 5 that the inclusion of the recognition memory judgment on each trial does not have a significant effect on priming.

Experiment 1

The goal of Experiment 1 was to address the three empirical questions laid out above that comprise the core of the research presented here: (a) to determine whether there is a repetition priming effect for nonword stimuli designed to be as nonwordlike as possible; (b) to compare the relative magnitude of priming effects for words, pseudowords, and nonwords; and (c) to determine whether explicit recollection of the stimuli could be eliminated as the sole source of any repetition effects found.

Method

Participants. Twenty-seven Carnegie Mellon University undergraduates participated in the experiment for course credit. Data from 3 participants were dropped for failing to maintain at least 80% nonerror trials. Error trials consisted of items misidentified at study or at test, or items for which the voice key triggered inappropriately at study or at test. Because these trials are removed from the analysis, high error rates result in insufficient data to form reliable estimates of performance in the various conditions.

Materials. A list of four-letter words was generated using the MRC database (Coltheart, 1981). Parameters for word selection were a Kučera and Francis (1967) score between 10 and 200; a maximum of 500 on the concreteness and imageability scales; and the exclusion of proper names, archaic terms, and colloquialisms. There were 307 words in the database that fit these parameters. A random selection of 153 of these items were used as potential words in the study, and the other 154 were used to generate pseudowords. After filtering these lists to remove items with initial vowels, pseudowords were created from the "proto-pseudoword" list by swapping the onsets of words with the same vowel and different codas (e.g., "wave" and "balm" become "bave" and "walm"), and removing any words or pseudohomophones that resulted. A total of 562 pseudowords were generated this way. A total of 7,920 nonwords were created by randomly sampling four letters from $\{k, g, d, p, b, z, v, f, x, q, j\}$ without replacement, creating highly unpronounceable letter strings. From these lists, three lists containing 20 items from each stimulus type were selected randomly without replacement (i.e., 60 items on A, B, and C lists). The average position-independent bigram frequency was calculated by using the MRC database and was found to be 5,846 for words, 5,348 for pseudowords, and 18.8 for nonwords, giving evidence that our pseudowords are orthographically similar to words and that our nonwords are highly dissimilar to words.

Procedure. The experiment took place in three phases: a study phase in which all participants were exposed to the 60-item A and B lists, a distraction phase, and a test phase in which the stimulus list varied between participants (either A and C or B and C). In the study phase, participants were told that the study was concerned with visual perception and that we were interested in the time it takes for them to accurately read letter strings presented on a screen. The task was the same for all participants and consisted of the identification portion of the CID-R task described above using 130 letter strings (10 initial practice strings in addition to the A and B lists). Participants were instructed that a four-letter string would appear on the screen for a very brief duration and be covered over almost immediately by a mask. The string would reappear and continue to flash on the screen for longer and longer durations, alternating with the mask, and making it appear as if the string became clearer with time. Participants were asked to name aloud the letters of the string from left to right as soon as they felt they had correctly identified all of the letters in the string. They were told that when their response began, the mask would reappear and the letter string would not be presented again. They were to go as quickly as possible while maintaining accuracy, and they were informed that they would be notified immediately if they misidentified an item. The instructions were, therefore, designed to minimize the number of misidentified items. Participants were also told that some of the letter strings might form words but that many of them would not and that their task was the same—to verbally identify the letters—no matter what string appeared.

Stimuli were presented on a Macintosh Quadra 660AV computer using PsyScope (J. Cohen, MacWhinney, Flatt, & Provost, 1993), and timing was accomplished with the PsyScope Button Box for 1-ms accuracy. Letter strings were presented in 18-point bold Courier typeface, subtending approximately 5° of visual angle. The mask was a row of pound signs (####) centered on the same location and presented in a slightly larger 24-point font. Each trial began with the presentation of the mask for 500 ms to orient the participant. The stimulus was then presented for 17 ms (the duration of one screen refresh), and the mask followed for 233 ms, making a 250-ms block. This stimulus presentation was repeated with the duration of the stimulus increasing by 17 ms every other presentation. The total stimulus plus mask time remained constant.

A voice key was used to stop the trial and measure RT. Trials in which the voice key triggered before the verbal response or failed to trigger were marked by the experimenter to be discarded in the test phase data as were trials in which the participant misidentified the stimulus. After identifying the string, the participant pressed a key to move onto the next trial. In the event of a misidentification, the experimenter said "incorrect" before the participant moved on. The first 10 items were filler items drawn from the same population as the actual list items but were not used as data so that the participant could become accustomed to the task.

After the participant identified all 130 items, the distraction phase began in which the participant filled out several forms and was allowed to rest. After approximately 5 min, the CID-R test phase began. In this phase, the

[1] As noted earlier, if a participant misidentifies a letter string at study or at test, that item is removed from all analyses.

Table 2
CID-R Reaction Times in Milliseconds

	Primed[a]				Unprimed			
Stimulus	S-old	P-old	P-new	S-new	S-old	P-old	P-new	S-new
Experiment 1								
Word	2,424		2,536		2,647		2,676	
Pseudoword	2,824		3,013		3,267		3,105	
Nonword	3,424		3,551		3,366		3,574	
Experiment 2								
Pseudoword	2,644	2,829	2,809	2,858	2,699	2,828	2,932	2,900
Nonword	3,069	3,153	3,253	3,264	3,160	3,164	3,271	3,336
Experiment 3								
Word	1,264	1,284	1,405	1,334	1,418	1,390	1,386	1,395
Pseudoword	1,511	1,591	1,625	1,630	1,631	1,823	1,732	1,747
Nonword	1,855	1,957	1,963	2,022	2,090	1,988	2,044	1,949
Experiment 4								
Word	2,012	2,297	2,395	2,179	2,202	2,428	2,412	2,295
Nonword	3,250	3,449	3,432	3,188	2,936	3,440	3,573	3,400
Experiment 5								
Word	2,107	2,157	2,136	2,246	2,170	2,279	2,314	2,252
Pseudoword	2,463	2,507	2,566	2,613	2,708	2,680	2,682	2,701

Note. CID-R = continuous identification with recognition; S-old = sure old; P-old = probably old; P-new = probably new; S-new = sure new.
[a] Experiment 1 used an old–new, two-choice recognition memory probe. Experiments 2–5 used a four-choice recognition memory probe. As responses were not evenly divided among the four categories, they were collapsed into two categories (old and new) for all data analyses.

participant was instructed that the task was virtually identical to the previous task except that some of the letter strings had appeared in the first part of the experiment and some had not. Instead of simply pressing a button to continue with the next item, a screen containing the phrase "old or new" would appear, and the participant was asked to appropriately press one of two keys, guessing if unsure. In all other regards, the test phase was identical to the study phase, including the use of several filler items at the outset (half old filler items and half new). Stimuli that were misidentified in either the study or the test phase were counted as errors (along with trials in which the voice key failed to trigger at the appropriate time) and were removed from the analysis.

Results

The raw RTs to identify stimuli in the test phase are shown for primed and unprimed items of each stimulus type as a function of recognition memory response in Table 2. Overall mean RT, priming effects, and recognition memory accuracy (d') are shown for all three stimulus types in Table 3. It is worth reiterating that the RTs shown do not reflect the time to generate a recognition memory response; rather, they are simply the time required to identify the stimuli. Mean RTs for each participant were calculated in each condition, and it is these means that are used in the data analysis. For all data analysis, an alpha level of .05 was used. Tests were two-tailed with one exception. When an overall priming effect was demonstrated for a stimulus type, tests for a priming effect on the subset of trials in which the participant responded "new" were one-tailed.

Overall, words were identified in 2,559 ms, pseudowords in 3,016 ms, and nonwords in 3,492 ms. A repeated measures analysis of variance (ANOVA) found a main effect for stimulus type, $F(2, 46) = 160$, and paired t tests found words were identified faster than pseudowords, $t(23) = 13.6$, which were faster than nonwords, $t(23) = 8.7$. The ANOVA also found a main effect for repetition, $F(1, 23) = 38$, and a Stimulus Type × Repetition interaction, $F(2, 46) = 4.8$.

When broken down by stimulus type, ANOVAs found that the 191-ms priming effect for words, $F(1, 23) = 31$, and the 203-ms priming effect for pseudowords, $F(1, 23) = 16$, were significant but that the 33-ms priming effect for nonwords was not, $F(1, 23) = 0.73$. Paired t tests on the magnitude of the repetition effects showed that the priming effect was larger for words than nonwords, $t(23) = 3.0$, and larger for pseudowords than nonwords, $t(23) = 2.5$. However, the size of the priming effects for words and pseudowords could not be differentiated, $t(23) = 0.20$.

When only those trials for which the participant responded "new" were considered, there was still a significant 140-ms priming effect for words, $t(23) = 2.0$, and a 92-ms effect for pseudowords, $t(23) = 1.7$. Nonwords showed a nonsignificant 35-ms effect, $t(23) = 0.47$. Post hoc analyses showed that overall RTs to identify stimuli to which the participants subsequently responded "old" were significantly faster than those that were called "new": words, $t(23) = 3.8$; pseudowords, $t(23) = 3.0$; nonwords, $t(23) = 3.1$.

Recognition memory performance was assessed by calculating d' for each participant in each stimulus category and found to be significantly above chance in all: words, $d' = 1.43$, $t(23) = 13.8$; pseudowords, $d' = 1.16$, $t(21) = 12.4$; nonwords, $d' = 0.31$, $t(22) = 6.2$. Further, recognition memory d' for words was significantly higher than d' for pseudowords, $t(21) = 2.2$, paired, which was significantly higher than d' for nonwords, $t(20) = 6.2$. In general, as d' increased, hit rates went up and false-alarm rates

Table 3
CID-R Priming Effects and Recognition Memory Accuracy

Stimulus	Mean RT (ms)	Priming effect	New-RN priming[a]	d' (hit, false-alarm rate)
Experiment 1				
Word	2,559	191*	140*	1.43* (.68, .19)
Pseudoword	3,016	203*	92*	1.16* (.54, .15)
Nonword	3,492	33	35	0.31* (.50, .37)
Experiment 2				
Pseudoword	2,813	105*	64*	0.86* (.61, .29)
Nonword	3,197	46*	26	0.34* (.55, .43)
Experiment 3[b]				
Overall				
Word	1,330	96*	64*	1.33* (.79, .35)
Pseudoword	1,650	137*	57*	1.13* (.57, .20)
Nonword	1,983	65*	40	0.41* (.47, .34)
ID				
Word	1,358	96*	44*	1.34* (.76, .30)
Pseudoword	1,665	137*	56*	1.01* (.49, .17)
Nonword	2,031	65*	88*	0.48* (.43, .28)
Pronounce				
Word	1,303	102*	85	1.32* (.82, .40)
Pseudoword	1,634	181*	57	1.24* (.64, .23)
Nonword	1,934	44	−9	0.34* (.51, .40)
Experiment 4				
Overall				
Word	2,159	142*	65*	1.79* (.74, .17)
Nonword	3,367	56*	141*	0.31* (.47, .36)
CID				
Word	2,123	78*		
Nonword	3,293	54*		
CID-R				
Word	2,194	208*	65*	1.79* (.74, .17)
Nonword	3,439	58*	141*	0.31* (.47, .36)
Experiment 5				
Overall				
Word	2,134	103*	80*	1.25* (.72, .31)
Pseudoword	2,520	137*	125*	0.93* (.50, .20)
CID				
Word	2,085	108*		
Pseudoword	2,456	119*		
CID-R				
Word	2,183	97*	80*	1.25* (.72, .31)
Pseudoword	2,585	161*	125*	0.93* (.50, .20)

Note. CID-R = continuous identification with recognition; RT = reaction time; RN = recognition; ID = identification; CID = continuous identification.
[a] Amount of repetition priming for only those items to which the participant responded "new" to the recognition memory probe. [b] Several presentation parameters were altered in Experiment 3 and resulted in an overall reduction in RT to identify the stimuli.
* $p < .05$.

went down[2] (Table 3), as revealed by the following analysis. A repeated measures ANOVA found not only main effects of both stimulus type, $F(2, 46) = 3.3$, and repetition, $F(1, 21) = 311$, on the probability of responding "yes" but also a significant interaction between the two, $F(2, 46) = 39$. Further, separate ANOVAs on the hit rates, $F(1, 23) = 9.8$, and false-alarm rates, $F(1, 23) = 17$, found significant linear contrasts for stimulus type. Thus, consistent with the literature (Glanzer & Adams, 1985, 1990; Glanzer, Adams, Iverson, & Kiosk, 1993), the data demonstrate a mirror effect.

For each stimulus category, the Pearson product–moment correlation comparing each participant's priming effect and d' was calculated. There was no evidence of a correlation for words, $r = .02$, $t(22) = 0.09$; pseudowords, $r = .17$, $t(20) = 0.78$; or nonwords, $r = -.11$, $t(21) = 0.52$.

Discussion

In Experiment 1, the CID-R task was used to assess both the time to identify and the accuracy of recognition memory for words, pseudowords, and nonwords following an incidental encoding task. Not remarkably, words were identified faster than pseudowords, and pseudowords were identified faster than non-

[2] In a recent report, Whittlesea and Williams (2000) demonstrated consistently higher false-alarm rates for pseudowords than for words. This was not the case in any of our experiments. False-alarm rates for words were numerically larger than those for pseudowords in all three experiments in which they were directly contrasted. The source of this discrepancy is not immediately apparent.

words. Similarly, recognition memory was most accurate for words, followed by pseudowords, and then nonwords.

More important, there was a clear repetition priming effect for both words and pseudowords. This result is in accord with previous demonstrations of priming for pseudowords (Bowers, 1994; Dorfman, 1994; Feustel et al., 1983; Rueckl, 1990; Rueckl & Olds, 1993; Salasoo et al., 1985; Whitlow & Cebollero, 1989) but with an important difference. Unlike these studies, use of the CID-R task allows us to reject the hypothesis that explicit recollection of the item during the test phase was the sole mechanism responsible for the priming effect. For both words and pseudowords, there was still an effect of repetition even if the participant claimed he or she had not seen the item. Further, recognition memory performance and priming were not significantly correlated. Explicitly recognizing a fragmentary or degraded letter string as one of the studied items cannot be the sole cause of a repetition effect.

The results presented here using the CID-R task add another converging line of evidence supporting the claim that priming can exist for "novel" items and not be the direct cause of recognition of the item during the priming task. These results do not support the hypothesis that all novel letter strings will demonstrate this effect, however. In contrast to Bowers's (1994) findings, although pseudowords showed a strong repetition effect, nonwords did not. Although it would be premature to conclude that nonwords cannot demonstrate any effect of repetition, it is clear from the data that the effect repetition has on pseudowords is far greater than the effect on nonwords.

Experiment 2

Three difficulties exist with Experiment 1 that are addressed in Experiment 2. First, it is quite possible that a small repetition effect exists for nonwords but that Experiment 1 lacked the power to resolve it. Although the magnitude of the repetition effect on nonwords was far smaller than that for words or pseudowords, the effect might still be reliable under more powerful testing conditions. Experiment 2 attempted to increase the power by doubling the number of test items, focusing only on pseudowords and nonwords, and by presenting all 120 study items at test. Additionally, which stimuli serve as study items and which stimuli serve as test items were counterbalanced across participants.

A second potential criticism of Experiment 1 is that it is possible for an effect of repetition to be induced in the "new" responses even if explicit recollection is the sole source of the priming effect. The possibility arises if participants have an explicit recollection of the stimulus but still respond "new" in the two-choice forced recognition memory task. If we suppose that participants can have explicit recollections that are somehow not complete or clear enough to be certain of their recognition memory, a bias to respond "new" on these trials would result in an induced priming effect in these "new" responses. Countering this possibility is easily accomplished by providing more alternatives in the recognition memory phase. By providing participants with four options, including categories for both certain and uncertain recognition memory, the problem is ameliorated. Note that for the purposes of data analysis, recognition memory responses were collapsed into two categories: old and new.[3]

One final criticism of the first study is that the amount of orthographic overlap within a stimulus type is uncontrolled. In Experiment 1, the probability of a word sharing two or more letters in the same position with any specific other word was .060. Pseudowords had a probability of .094, and nonwords had a probability of .048. Previous research has demonstrated that words and pseudowords can prime orthographically similar items (Feustel et al., 1983; Rueckl, 1990), suggesting that if the assignment of orthographically similar items to the primed and unprimed lists were not perfectly balanced, then we could induce priming effects that would distort our comparison of priming among the three stimulus types. For example, if *gave* and *save* were on one list (primed half of the time and unprimed the other half) and *wish* and *fish* were on the other list, then the amount of priming for words would be greater than if *gave* and *wish* were on the same list and *save* and *fish* were on the other. To the extent that the different stimulus types have different amounts of within-type overlap, the opportunity for such distortion of the priming effect sizes will differ. In Experiment 2, a new stimulus generation procedure was used in which an algorithm generated nonwords directly from the pseudoword stimuli used in the experiment. This modification fully balances the amount of within-category overlap among stimuli and allows us to make more accurate comparisons of the relative priming magnitudes.

Method

Participants. Twenty-four Carnegie Mellon University undergraduates participated in the experiment for course credit. None of the participants had been used in Experiment 1.

Materials. The population of pseudowords used in Experiment 1 was filtered to remove any items containing $\{w, x, k, q, j, g\}$. Vowels in the pseudowords were then replaced with this set of letters, and the order was rearranged by swapping Letter Positions 1 and 3 and Positions 2 and 4 to create pairs of pseudowords and nonwords. This method guarantees identical within-group orthographic overlap for pseudowords and nonwords. These lists were then sampled to create the two lists (A and B) of 60 items of each stimulus type.

Procedure. The design was identical to Experiment 1 except in regard to stimulus list assignment (Table 1). Participants were alternately assigned to receive either the A list or the B list during study. All participants received the combination of the A and B lists at test. Unlike Experiment 1, all study items were present at test.

The study procedure was the same CID-R task used in Experiment 1 except that because no words were used, participants were not told words would be on the list. The distraction phase was changed to a digit-span task to guarantee at least 10 min between study and test and to ensure all working memory for the study list had been eliminated. Participants worked through a list of 10 seven-digit and 10 eight-digit number sequences (presented one digit at a time), attempting to immediately recall the digits after the last one was presented.

The CID-R task used in Experiment 1 was used here at test with one modification. Four choices were given for the recognition memory judgment: (*fairly sure old, probably old but unsure, probably new but unsure,*

[3] The use of four-choice recognition was dictated by the possibility of inducing a priming effect in the "new" responses when participants were not allowed an intermediate "unsure" response. An attempt was made to analyze the data for each of the four recognition response categories. Unfortunately, this attempt was unsuccessful and was due to uneven numbers of responses in the four categories. Responses within an individual participant were not divided equally enough to successfully estimate the means in the resulting eight possible categories (four recognition by two old/new).

and *fairly sure new*). All 120 studied items and 120 unstudied items were presented in random order after 10 filler items.

Results

The raw RTs to identify stimuli in the test phase are shown for primed and unprimed items of each stimulus type as a function of recognition memory response in Table 2. It is worth reiterating that although four recognition memory responses were available to participants, the data were collapsed into two levels: old (sure and probable) and new (sure and probable) during all data analysis (see Footnote 3). Overall mean RT, priming effects, and recognition memory accuracy (d') are shown for both stimulus types in Table 3, and the sources of data loss are shown in Table 4.

Overall, participants had a mean RT of 2,813 ms to identify pseudowords and 3,197 ms to identify nonwords. A repeated measures ANOVA found a main effect of stimulus type, $F(1, 23) = 127$, and repetition, $F(1, 23) = 18.8$. The Type × Repetition interaction was marginally significant, $F(1, 23) = 3.7$, $p = .067$.

The 105-ms overall repetition effect for pseudowords, although apparently smaller than that found in Experiment 1, was still significant, $F(1, 23) = 16.2$. The overall 49-ms repetition effect for nonwords was also significant, $F(1, 23) = 6.6$. As noted, the interaction term in the ANOVA did not reach the traditional significance criterion and failed to support a difference between the two priming effects. However, when subjected to a paired one-tailed t test, priming was greater for pseudowords, $t(23) = 1.93$.

When only the trials to which the participant later responded "new" are considered, there was still a significant 64-ms repetition effect for pseudowords, $t(23) = 2.0$, and a nonsignificant 26-ms effect for nonwords, $t(23) = 0.96$. As in Experiment 1, RTs to identify the string were faster for trials subsequently judged as "old" than for trials judged "new" for both stimulus types: pseudowords, $t(23) = 4.0$, and nonwords, $t(23) = 3.7$.

Recognition memory performance in terms of d' was significantly above chance for both pseudowords, $d' = 0.86$, $t(23) = 12.8$, and nonwords, $d' = 0.34$, $t(23) = 5.7$, with pseudoword recognition memory performance being significantly better, $t(23) = 6.9$. The post hoc correlation between priming effect size and d' was calculated for each stimulus type. Pseudowords showed no significant correlation, $r = .02$, $t(22) = 0.1$, but nonwords showed marginal evidence for a positive correlation, $r = .33$, $t(22) = 1.66$, $p = .055$. In general, as d' increased, false-alarm rates went down, and hit rates had a tendency to be higher (Table 3), consistent with the basic mirror effect. The repeated measures ANOVA found the interaction between stimulus type and repetition on the probability of responding "yes" to be reliable, $F(1, 23) = 47$. Paired t tests demonstrated higher false-alarm rates for nonwords relative to pseudowords, $t(23) = 3.4$, but did not demonstrate reliably higher hit rates for pseudowords relative to nonwords, $t(23) = 1.4$, $p = .18$.

Discussion

Overall, the results of Experiment 2 are consistent with those of Experiment 1. Pseudowords still showed a significant priming effect both overall and on trials in which the participant responded "new" to the recognition memory probe. The increased power of Experiment 2 allows us to demonstrate that there is a priming effect for nonwords but that it is significantly smaller than that for pseudowords. This finding is important, for it demonstrates that letter strings designed to be highly nonwordlike can show repetition effects.

Table 4
Sources of Data Loss

	Study		Test		
Stimulus	V-key[a]	ID[b]	V-key[a]	ID[b]	% data analyzed[c]
Experiment 1					
Word	—	—	—	—	94.5
Pseudoword	—	—	—	—	94.9
Nonword	—	—	—	—	84.4
Experiment 2					
Pseudoword	0.28	1.9	1.5	0.45	96.5
Nonword	0.07	5.1	0.83	2.7	93.9
Experiment 3					
Word	0.38	0.13	4.6	0.26	94.9
Pseudoword	0.77	0.83	4.7	1.1	93.4
Nonword	0.96	3.1	3.9	6.1	87.9
Experiment 4					
Word	0.64	0.43	2.5	0.45	96.5
Nonword	1.0	6.2	1.9	4.6	89.8
Experiment 5					
Word	0.67	1.3	2.3	0.05	95.9
Pseudoword	1.0	4.0	2.4	3.0	92.2

Note. Dashes indicate that data were not available. V-key = voice key; ID = identification.
[a] Numbers are the percentage of trials of each type in which the voice key failed to trigger properly. These items were excluded from the data analysis. [b] Numbers are the percentage of trials of each type in which the participant misidentified the letter string. These items were excluded from the data analysis. [c] This indicates the total percentage of trials in which data were analyzed for each stimulus type (i.e., the percentage of trials in which there were no errors at study or at test).

There are two things of note concerning the nonword repetition effect, however. First, the effect is not nearly as strong as that for other novel stimuli that share the orthographic structure of words (i.e., pseudowords). Second, we cannot be confident that the effect is not the result of explicit recollection speeding identification times. The 29-ms priming effect in the "new" responses was not strong enough to reach a clearly significant level. These results therefore do not strongly support priming in the absence of recognition memory. Further, participants' priming effects and recognition memory accuracies showed some degree of positive correlation. Taken together, these two results raise concerns similar to those in Bowers's (1994) data as to whether the repetition effect for nonwords is truly the result of implicit memory or is mediated solely by explicit memory.

One final result worth noting is that the pseudoword d' and priming effect sizes are noticeably smaller here than in Experiment 1. It is quite possible that either the increase in list length at test or the lack of word stimuli may have changed the way in which participants processed pseudowords at either study or test. A post hoc comparison of d' and priming effects for the first and second half of the data gave no support for the former possibility. At the halfway point in the test phase, participants had studied and been tested on as many items as were in Experiment 1. This half of the data did not significantly differ from the latter half of the data in terms of d' or priming effect, suggesting that a general falloff in performance with experiment duration is not the source of the reduced priming effect. Further, nonword performance appears identical to that found in Experiment 1.

The removal of words in Experiment 2, though, remains a possible cause for the reduction in the priming effect. Although a number of studies have failed to find effects of study task manipulations on priming, several studies have reported level of processing effects on priming (Brown & Mitchell, 1994; Challice & Brodbeck, 1992; but see Hamann & Squire, 1996). It is quite possible that participants process pseudowords differently when words are included in the experiment versus when nonwords are the only other stimuli. For example, participants may be more likely to "read" a pseudoword and internally generate a phonological representation if words are present on the list, and this could potentially influence priming.

Experiment 3

Experiment 2 demonstrated that with increased power of our statistical tests, a small repetition effect can be found for nonwords. The effect is significantly smaller than that for pseudowords and is still unreliable when the potential effect of explicit recollection is removed by examining priming for only those items judged as "new." In Experiment 3, the stimulus generation procedure is refined even further in an attempt to increase our ability to detect priming for nonwords in the absence of explicit recollection.

As one of the goals of this research is to compare priming across stimulus types, we returned to a fully mixed stimulus design in Experiment 3. The issue of controlling within-stimulus-type overlap that was raised in Experiment 2 is extended here to include the word stimuli as well. Pseudoword and nonword stimuli were generated directly from the specific pairs of word stimuli used in the experiment so that the amount of within-category overlap among stimuli is fully balanced. This balancing is required to make valid comparisons of priming across categories.

A final aim of Experiment 3 is to explore the role played by the study task on the two measures of the CID-R task. In both Experiments 1 and 2, the study and test tasks were very similar; the study task was merely a subset of the test task. This similarity between study and test is atypical of most implicit memory experiments (traditional test tasks such as t-scope perceptual identification and fragment completion are not well suited for use as study tasks because the participant may not generate the to-be-studied item). To ensure that the priming we have measured in the CID-R task is not the result of this similarity between study and test, Experiment 3 uses a between-subjects manipulation of study task. One task in Experiment 3 is the CID task used in Experiments 1 and 2, and the other is a nonspeeded identification and pronounceability rating task.

Method

Participants. Fifty-two Carnegie Mellon University undergraduates participated in the experiment for course credit. None of the participants had been used in either of the earlier experiments.

Materials. To more tightly control for potential effects of orthographic overlap among letter strings, the stimulus generation procedure was refined in Experiment 3. The list of potential word stimuli from Experiment 1 was taken and filtered to remove all words beginning with a vowel, having doubled letters, or containing the consonants {*w, x, k, q, j,* or *g*}. These consonants served as "replacement vowels" for creating nonwords. Words were paired on the basis of shared vowels, and their onsets were swapped to create a pair of pseudowords. Thus, the pair *hate* and *vast* would become *vate* and *hast.* The word pairs were also used to create nonwords by replacing {*a, e, i, o, u,* and *y*} with {*w, x, k, q, j,* and *g*}, respectively, and reordering the letter positions 3-1-4-2. Thus, this word pair would become *thxw* and *svtw.* The entire list of words, pseudowords, and nonwords was then filtered so that within a stimulus type, no two items shared three letters in the same position. The stimulus pairs were then broken and assigned to one of two stimulus lists, A or B. In the present example, *hate, hast,* and *svtw* would be assigned to one list and their pairs to the other. A total of 30 words, 30 pseudowords, and 30 nonwords were on each list.

Procedure. The procedure for Experiment 3 was very similar to that used in the previous experiments (Table 1). As in Experiment 2, participants were shown stimuli from one of the two lists (A or B, counterbalanced across participants) during the study phase and both lists in the test phase. Unlike Experiment 2, the study phase was varied between participants. In one condition, the identification (ID) condition, the same CID task used in Experiments 1 and 2 was used. In the other condition, the pronounceability condition, participants were instructed that they would be shown a list of four-letter strings and that they should first identify the string by naming all four letters aloud. After naming the letters, they were to rate the string on its ease of pronunciation by pressing one of four keys (labeled 1–4). As with Experiment 1, participants were told that some letter strings would form words but that some of them would not and whether the string formed a word was irrelevant to their task.

The same digit-span task used in Experiment 2 was used here as a distraction task. Similarly, the same test task, the four-choice CID-R was used here, this time with a random ordering of all 180 items.

Experiment 3 was conducted on a Macintosh IIcx instead of the Quadra 660AV used in Experiments 1 and 2. To compensate for the IIcx's slower processing and video capabilities, several presentation parameters were modified in an attempt to maintain the same level of stimulus degradation. Most of note, the overall time window was reduced from 250 ms to 200 ms. Unfortunately, this makes direct comparison of RTs to RTs in other experiments impossible.

Results

The raw RTs to identify stimuli in the test phase are shown for primed and unprimed items of each stimulus type as a function of recognition memory response in Table 2. Overall mean RT, priming effects, and recognition memory accuracy (d') are shown for all three stimulus types in Table 3, and the sources of data loss are shown in Table 4.

Although the RTs overall are faster than in the previous experiments, the same central pattern is found. On average, words were identified in 1,330 ms, pseudowords in 1,650 ms, and nonwords in 1,983 ms. A repeated measures ANOVA found the stimulus type to have a significant main effect on RT, $F(1, 50) = 174$. Paired t tests showed that words were identified faster than pseudowords, $t(51) = 13.6$, which were identified faster than nonwords, $t(51) = 10.7$.

The ANOVA found a strong main effect of repetition, $F(1, 50) = 51$, but no evidence for a main effect of study condition on RT, $F(1, 50) = 0.18$. The interaction between stimulus type and repetition was significant, $F(2, 100) = 3.8$, as was the three-way interaction between stimulus type, repetition, and study condition, $F(2, 100) = 3.1$. No other interactions were significant.

When analyzed separately by stimulus type, we found a 96-ms repetition effect for words, $F(1, 50) = 26.7$; a 137-ms repetition effect for pseudowords, $F(1, 50) = 56$; and a 65-ms repetition effect for nonwords, $F(1, 50) = 7.3$. We used paired t tests on the repetition effect to find a significant difference between pseudowords and nonwords, $t(51) = 2.5$. The other comparisons showed no significant difference between words, pseudowords, and nonwords: $t(51) = 1.73, p = .09$ (for words vs. pseudowords), and $t(51) = 1.12, p = .27$ (for words vs. nonwords).

In the analysis of the pseudowords, we found the source for the three-way interaction between stimulus type, repetition, and study condition noted above. There was a significant interaction between repetition and study condition for pseudowords only, $F(1, 50) = 5.8$, with the ID condition showing a significantly smaller 93-ms repetition effect than the 181-ms effect in the pronounceability condition. Words showed a similar pattern of 89 ms and 102 ms, $F(1, 50) = 0.15$, and nonwords showed the opposite trend with 86 ms and 44 ms, $F(1, 50) = 0.76$.

When only the items to which the participants responded "new" in the recognition memory portion were considered, there was still a 64-ms repetition effect for words, $t(49) = 1.7$, and a 57-ms effect for pseudowords, $t(51) = 2.0$, but only a nonsignificant 39-ms effect for nonwords, $t(51) = 0.98$. Interestingly, for nonwords the size of the repetition effect for "new" responses varied with study task. Participants in the ID condition showed a significant 88-ms repetition effect, $t(25) = 1.9$, whereas participants in the pronounceability condition showed no significant repetition effect with a -9.3-ms difference between repeated and unrepeated items, $t(25) = -0.14$.

Recognition memory performance was again well above chance for all stimulus sets. Overall, words had a recognition memory d' of 1.33, $t(49) = 18$; pseudowords had a d' of 1.13, $t(50) = 14.3$; and nonwords had a d' of 0.41, $t(50) = 7.4$. Recognition memory for words was significantly better than for pseudowords, $t(49) = 2.5$, which was in turn significantly better than nonwords, $t(50) = 9.1$. There was no effect of study condition on the d' results for any of the stimulus types. In general, as d' increased, hit rates went up but false-alarm rates remained constant (Table 3). A repeated measures ANOVA found a significant interaction between repetition and stimulus type on the probability of responding "yes," $F(2, 102) = 70$, but separate ANOVAs revealed that although there was an increase in hit rates, linear contrast $F(1, 51) = 118$, there was no change in the false-alarm rate, linear contrast $F(1, 51) = 0.3$.

For each stimulus category, the Pearson product–moment correlation comparing each participant's priming effect and d' was calculated. There was no evidence of a correlation for words, $r = -.08$, $t(48) = 0.59$; pseudowords, $r = .18$, $t(49) = 1.29, p = .1$; or nonwords, $r = .05$, $t(49) = 0.36$.

Discussion

The overall results from Experiment 3 are consistent with the prior experiments. Again, words were identified fastest and were recognized with the greatest accuracy; nonwords were identified slowest and were recognized with the least accuracy. Significant repetition effects were found for words, pseudowords, and nonwords, reaffirming the potential for nonwords to show a repetition effect. The effect of repetition was significant again for words and pseudowords even when participants failed to recognize the item, allowing us to reject the hypothesis that explicit recollection was the only source of facilitation.

For nonwords, we found reliable priming in the "new" responses in one of the study conditions and no correlation between recognition memory accuracy and priming. Participants in the ID condition showed a significant "new" priming effect, though participants in the pronounceability condition showed no such effect. Why this should occur is unclear because the pronounceability condition is in many ways a superset of the ID condition. The results from the ID condition demonstrate for the first time, however, that nonwords can show priming even when there is no explicit recollection for the item.

The study task had only one effect on the results. Specifically, the pronounceability rating task enhanced priming of pseudowords relative to the ID condition. This result provides additional support for the hypothesis presented in the discussion of Experiment 2 that "reading" a pseudoword or somehow computing a phonological representation of it can result in greater priming. Although this result demonstrates the potential variability in the magnitude of the pseudoword priming effect, the overall accord between the two study tasks is such that we can be confident in using CID as a study task. Because both the task itself and the responses made are equivalent across stimulus type in CID, we view it as the overall superior task.

An unfortunate result of the change in experimental equipment is that the overall RTs in Experiment 3 were almost half the RTs found in the earlier experiments. Not only does this prevent the direct comparison of RTs between this experiment and the earlier ones but it appears to have affected the priming results as well. The ID condition of Experiment 3 is very similar to Experiment 1. Apart from the change in presentation parameters to accommodate different equipment, the only differences between the two are the equalization of within-type orthographic overlap across types and in the larger number of stimuli. Yet, in Experiment 3 the priming effect for words is half as large as that found in Experiment 1, and the priming effect for pseudowords is two thirds as large. One possibility is that a floor effect in overall RT in this task has compressed the priming effect for the fastest items. This could explain why the priming effect for words, though numerically still larger, was not reliably different than the priming effect for nonwords—a finding that runs counter to the clear difference found in Experiment 1. A potential source of the reduced priming effect for words in this experiment is explored in the computational model of repetition priming presented later (see *Hebb rule simulations*).

Experiment 4

In Experiment 3, we found the first evidence for priming of nonwords when participants responded "new" to the recognition memory probe. Although the previous experiments suggested such an effect, the CID condition in Experiment 3 was the first time the effect reached a significantly reliable level. To ensure that this finding is not an artifact, the first goal of Experiment 4 is to replicate this strong form of priming so that we can be sure priming of nonwords exists in the absence of recognition memory.

This replication is further motivated by an analysis of the nonwords used in Experiments 2 and 3. One of the stated goals of this research is to determine the extent of priming for novel information by examining priming of nonwords designed to be as dissimilar to words as possible. Unfortunately, although the nonwords used in Experiment 1 were constructed in such a way as to ensure a low bigram frequency (frequency of occurrence of letter pairs in English words), this constraint was not imposed explicitly in either of the other experiments (although the letter strings were still designed to be difficult to pronounce). In Experiments 2 and 3, we imposed constraints designed to minimize the amount of within-stimulus orthographic overlap and to equate this overlap across stimulus types. In so doing, the nonwords became more wordlike. The average bigram frequency for nonwords increased from 18.8 in Experiment 1 to 940 and 778 for Experiments 2 and 3, respectively. In Experiment 2, the worst example, *qtst*, had a bigram frequency of 4,945. For comparison, the words and pseudowords used in these experiments had mean bigram frequencies ranging from 5,348 to 5,846. Although these nonwords are still less orthographically similar to words than their pseudoword counterparts, we cannot ignore the fact that the more wordlike nonwords in Experiments 2 and 3 showed repetition effects and those in Experiment 1 did not. Therefore, we cannot be confident that the priming found in these two experiments was not the result of priming similar words or parts of words—a central question of this research. In Experiment 4, we addressed this issue by balancing both the overlap constraints and the need for very nonwordlike nonwords.

In addition, Experiment 4 was designed to clarify the relative status of priming for words and nonwords. Although Experiment 1 showed far larger priming for words than nonwords, Experiment 3's numerically larger priming was not significantly larger when raw RT was used in the analysis (though it was when the baseline differences in RTs were eliminated). Although the proposed compression of priming resulting from a floor effect in RT is a plausible explanation, we would do well to remove the potential floor effect and provide a direct comparison of priming for the two.

Finally, all the experiments so far have used CID-R as the test task. Although the use of only the "new" response trials can demonstrate the existence of priming in the face of recognition memory failure, one could argue that by including the recognition memory task on each trial, we are no longer generating a valid assessment of repetition priming or "implicit" memory. In being aware of the manipulation, participants may approach the task differently and may have a different source for the repetition effect (see Bowers & Schacter, 1990). In Experiment 4, we addressed this issue by contrasting the CID-R test task with CID—the same task without the recognition memory probe. Because we presume recognition memory might influence RT and priming (Graf, Shimamura, & Squire, 1985), we might expect slightly inflated overall priming when recognition memory occurs. Therefore, the CID-R task will be called into question if the priming of the "new" responses is larger than the overall priming found with CID.

Method

Participants. Sixty Carnegie Mellon University undergraduates participated in the experiment for course credit. None of the participants had been used in any of the earlier experiments.

Materials. The list of potential word stimuli from Experiment 1 was taken and filtered to remove all words beginning with a vowel, having doubled letters, or containing the letters {*w, x, k, q, j, g, v,* or *z*}. These consonants served as replacements for {*a, e, i, o, u, y, s,* and *t*} when creating nonwords. Words were further filtered to remove any with the same letter repeated anywhere in the word. Nonwords were created from these words by replacing the letters and rearranging the order 3-1-4-2. Word–nonword pairs were then filtered to remove any pairs whose nonword had a cumulative position independent bigram frequency greater than 200 according to the MRC database (Coltheart, 1981). Finally, the entire list of words and nonwords was then filtered so that within a stimulus type, no two items shared three letters in the same position. The procedure resulted in two lists of 39 words and 39 nonwords and six filler items with mean bigram frequencies of 5,638 and 50, respectively.

Procedure. The procedure for Experiment 4 was very similar to that used in the previous experiments (Table 1). As in Experiments 2 and 3, participants were shown stimuli from one of the two lists during the study phase and both lists in the test phase. The study phase consisted of the CID task used previously, counterbalancing the assignment of list to studied or not studied across participants. The same digit-span task was used here as a distraction task as well.

In the test phase, participants were given either the CID-R task or the CID task on all 78 items (plus initial fillers). The CID-R task was identical in design and instruction to the previous experiments. In the CID test condition, participants were told they would be doing a task very similar to the task used in the first part of the experiment, but that in this version they would no longer be given feedback if they incorrectly identified an item. As with the CID-R condition, they were informed that there would be more items on this list as well; however, they were not informed of the repetition manipulation.

Finally, in both tasks, we returned to a computer with sufficiently fast video capabilities to reengage the stimulus presentation parameters used in Experiments 1 and 2. This was done to elevate the overall RTs and remove the potential floor effect.

Results

The raw RTs to identify stimuli in the test phase are shown for primed and unprimed items of each stimulus type as a function of recognition memory response in Table 2. Overall mean RT, priming effects, and recognition memory accuracy (d') are shown for all three stimulus types in Table 3, and the sources of data loss are shown in Table 4.

On average, words were identified in 2,159 ms and nonwords in 3,293 ms. A repeated measures ANOVA found the stimulus type to have a significant main effect on RT, $F(1, 58) = 569$. The ANOVA found a strong main effect of repetition as well, $F(1, 58) = 67$, but no evidence for a main effect of test condition on RT, $F(1, 58) = 0.51$. The interaction between stimulus type and repetition was significant, $F(1, 58) = 7.7$, demonstrating the 143-ms overall priming effect for words to be larger than the 56-ms effect for nonwords. The ANOVA also found a significant interaction between test condition and repetition, $F(1, 58) = 7.4$, and a three-way interaction between stimulus type, repetition, and test condition, $F(1, 58) = 5.3$.

When analyzed separately by test condition, the source of these two interactions is apparent. There were statistically identical 54-ms (CID) and 58-ms (CID-R) priming effects for nonwords, $t(58) = 0.1$, in the two tasks. Words produced a 78-ms priming effect in the CID task and a larger 207-ms effect in the CID-R task, $t(58) = 4.2$. Unlike any of the prior experiments, "yes" recognition memory responses showed a very large effect of repetition (235 ms) with hits being identified exceptionally rapidly (2,055 ms). A separate ANOVA on the CID-R data found the Type × Response × Repetition interaction to be highly significant, $F(1, 27) = 22.8$. Further, when broken down by stimulus type, the Response × Repetition interaction was significant both for words, $F(1, 29) = 11.0$, and nonwords, $F(1, 29) = 4.3$.

When only the items to which the participant responded "new" in the recognition memory portion of the CID-R task were considered, there was still a 65-ms repetition effect for words, $t(27) = 2.4$, and a 141-ms effect for nonwords, $t(29) = 3.6$. The word and nonword priming effects for "new" responses did not reliably differ, $t(27) = 1.98, p = .06$. Additionally, although words had shown an effect of test condition on overall priming, the priming effect in the "new" responses for words did not differ from the priming effect found in the CID task, $t(56) = 0.36$.

Recognition memory performance was again above chance for both stimulus types. Words had a recognition memory d' of 1.8, $t(29) = 18.8$, and nonwords had a d' of 0.31, $t(29) = 6.1$. Recognition memory for words was significantly better than recognition memory for nonwords, $t(29) = 14.41$. For each stimulus category, the Pearson product–moment correlation comparing each participant's priming effect and d' was calculated. There was no evidence of a correlation for words, $r = -.06$, $t(28) = 0.32$, or nonwords, $r = .18$, $t(28) = 0.9$. In general, as d' increased, hit rates went up and false-alarm rates went down (Table 3), demonstrating a mirror effect. The repeated measures ANOVA found the interaction between stimulus type and repetition on the probability of responding "yes" to be reliable, $F(1, 29) = 266$. Paired t tests demonstrated higher hit rates for words relative to nonwords, $t(29) = 7.0$, and higher false-alarm rates for nonwords relative to words, $t(29) = 4.8$.

Discussion

Experiment 4 had three main goals: (a) to replicate the finding of nonword priming both overall and in the "new" responses using more nonwordlike nonwords, (b) to determine whether words would again show more priming than nonwords once the RTs were lifted off the floor, and (c) to determine whether the introduction of the recognition memory probe in the CID-R task qualitatively affects the results. The first two goals were clearly achieved. Priming was found for nonwords both overall and in the "new" responses using exceptionally nonwordlike stimuli. Participants were faster to identify repeated nonwords even when they failed to recognize the items immediately after identification. In addition, although repetition priming was found for nonwords, it was smaller in magnitude than priming for words.

The third goal was less clearly met because the word-priming effect was larger in the CID-R task than in the CID task. The source of this difference was an exceptionally fast mean RT to identify primed items that were recognized in the CID-R task (hits = 2,055 ms). This led to a larger priming effect for the "old" responses (235 ms) than the "new" responses (65 ms). This behavior is highly atypical of the results from all the previous experiments. In general, "old" responses are faster than "new" responses, but the priming effects are similar. Unfortunately, in Experiment 4, the data from the CID-R task on words show a possible effect of explicit recollection unlike anything seen in any of the prior experiments. That said, the critical comparison between overall priming in the CID task and "new" priming in the CID-R task (which, we propose, is free of contamination by explicit recollection) showed no difference. From this we can conclude that recognition memory might influence priming in the CID-R task but that the task itself can indicate whether the contamination is likely to exist and can still provide evidence for priming that is free of this contamination.

Precisely why participants in the CID-R task showed this somewhat odd behavior for words in this experiment is not clear from the data at hand. One potential explanation is that the striking difference in ease of identification between the two sets of stimuli resulted in a strategy we had not seen earlier. Without the intermediate case of pseudowords, participants may have been more likely to use their explicit memory for words to guide their perception of the stimuli. Without pseudoword stimuli, participants can assume that any wordlike string must be an English word. It is plausible that participants began their identification response to word stimuli before it had been fully identified, filling in any missing letters based on their explicit memory of the study items (as well as their knowledge of English words). As a result, such anticipatory responses would serve to artificially reduce the RT to hits disproportionately for the word stimuli. From these data, however, such arguments must remain purely speculative.

Experiment 5

In addressing the question of the relative magnitude of priming effects across stimulus types, one relationship is still unclear from the data in Experiments 1–4: the relationship between word and pseudoword priming. In both relevant experiments, pseudoword priming was numerically larger than word priming, and in Experiment 3, the difference was marginally significant. Further, in results from a study not presented here, pseudowords showed almost twice as much priming as words. Unfortunately, because of the stimulus generation procedures, it is unclear whether pseudowords actually show larger priming effects than words or whether words could be enhancing the effect on pseudowords through cross-stimulus-type priming.

The difficulty is shown in Figure 2A. In Experiment 3, pseudowords were generated from word pairs to equate the amount of within-stimulus-type overlap. When words and pseudowords were assigned to primed and unprimed lists, a word and the pseudoword containing the other word's onset were grouped together. This was done so that words and pseudowords would not share the same initial letters. Unfortunately, this method results in the potential for cross-stimulus-type priming between words and pseudowords as the primed pseudowords have primed word neighbors.[4] At test, the pseudoword *lave* could show priming both as a result of its repetition and as a result of exposure to *wave*. Although the converse holds true as well, the compression of priming effects for faster RTs would result in an artificially larger priming effect for the overall slower pseudowords. From the current data, we cannot know whether such cross-stimulus-type priming is a factor in pseudoword priming.

In addition to addressing the issue of overlap in word and pseudoword priming, Experiment 5 provides another comparison of the CID and CID-R tasks. Recall that in Experiment 4, the behavior of participants in the CID-R task was atypical and showed larger effects of recognition memory on RT than previously seen. Experiment 5 repeats the comparison of the two tasks to determine whether the differences between CID and CID-R are replicable when pseudowords are included in the test list such that a partial match with a studied word will not provide sufficient information for identification.

Method

Participants. Sixty Carnegie Mellon University undergraduates participated in the experiment for course credit. None had participated in any of the earlier experiments.

Materials. The list of potential word stimuli from Experiment 1 was not sufficient to generate enough stimuli for this experiment. A new population of words was generated from the MRC database without the imageability and concreteness constraints used in the original selection. All other parameters remained the same, and the result was a list of 629 words. This list was filtered to remove items with two identical letters anywhere in the word and items with an initial vowel. Words were then paired as before on the basis of matching vowels, and onsets were swapped to form a pair of pseudowords from the pair of words. Word–pseudoword quads were then filtered to remove any whose pseudowords were actual words or obvious pseudohomophones. From this set, three lists of 25 word–pseudoword quads (A, B, C) were selected such that no two items within a stimulus type could share three letters in common in the same position.

Procedure. The between-participant component of Experiment 5 was a 2 × 3 × 2 design. One factor was which member of each pair was primed and which was unprimed. The three-level factor consisted of which list (A, B, or C) provided the high-overlap stimuli and which list provided the low-overlap stimuli. For example, if List A provided the high-overlap stimuli, it would donate both words and pseudowords. Participants in this condition would have low-overlap words donated from the words of List B and low-overlap pseudowords donated from List C. Which list donated which stimuli was fully counterbalanced across participants. The final between-participant factor, test task, consisted of either CID or CID-R tasks at test. The result was a total of 12 fully counterbalanced participant groups. Stimulus type (words or pseudowords) was the one within-participant factor.

The procedure for Experiment 5 was identical to that used in Experiment 4 except that 100 items (25 low-overlap words, 25 high-overlap words, 25 low-overlap pseudowords, and 25 high-overlap pseudowords) were presented at study and 200 items were presented at test (see Table 1).

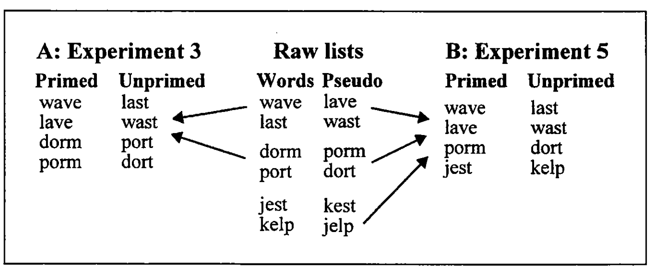

Figure 2. Word and pseudoword list generation procedures for (A) Experiment 3 and (B) Experiment 5 demonstrating the potential for within-stimulus-type neighborhood priming effects.

Results

The raw RTs to identify stimuli in the test phase are shown for primed and unprimed items of each stimulus type as a function of recognition memory response in Table 2. Overall mean RT, priming effects, and recognition memory accuracy (d') are shown for all three stimulus types in Table 3, and the sources of data loss are shown in Table 4.

On average, words were identified in 2,134 ms and pseudowords in 2,520 ms. A repeated measures ANOVA found stimulus type to have a significant main effect on RT, $F(1, 58) = 332$. The ANOVA found a strong main effect of repetition as well, $F(1, 58) = 125$, but no evidence for a main effect of test condition, $F(1, 58) = 0.52$, or overlap, $F(1, 58) = 0.06$, on RT. The interaction between stimulus type and repetition was significant, $F(1, 58) = 4.2$, demonstrating the 103-ms overall priming effect for words to be smaller than the 137-ms effect for pseudowords. However, if the baseline differences are removed and percentage change in RT is used to assess priming, this difference is not significant, $t(59) = 0.71$.

The ANOVA also found equal priming in the CID and CID-R tasks in the form of No Test × Repetition interaction, $F(1, 58) = 0.73$. The three-way interaction between stimulus type, repetition, and test condition was found to be marginally significant, $F(1, 58) = 3.3, p < .075$. Paired t tests showed the source of this interaction to be a larger priming effect for pseudowords over words in the CID-R task, $t(29) = 3.2$, but not in the CID task, $t(29) = 0.2$. No other interactions in the ANOVA were significant, including the Type × Overlap × Repetition interaction, $F(1, 58) = 1.6, p = .21$.

A separate ANOVA was calculated by using a response factor in place of the overlap factor. Unfortunately, because this factor further divides the data and because responses are not evenly distributed, this ANOVA is less powerful and cannot be used in the general case. This ANOVA found only main effects of type, $F(1, 29) = 219$; response, $F(1, 29) = 4.4$; and repetition, $F(1, 29) = 33.7$, but no significant interactions.

When only the items to which the participants responded "new" in the recognition memory portion of the CID-R task are consid-

[4] Although the nonwords were also generated from the words, the combination of reordering to 3-1-4-2 and vowel replacement effectively eliminates the concern here.

ered, there was still an 80-ms repetition effect for words, $t(27) = 3.2$, and a 125-ms effect for pseudowords, $t(29) = 5.2$.

Recognition memory performance was again above chance for both stimulus types. Words had a recognition memory d' of 1.25, $t(29) = 13.8$, and pseudowords had a d' of 0.93, $t(29) = 12.9$. Recognition memory for words was significantly better than recognition memory for pseudowords, $t(29) = 3.7$. In general, as d' increased, both hit rate, $t(29) = 7.9$, and false-alarm rate, $t(29) = 3.7$, increased (Table 3), failing to demonstrate a mirror effect. However, the repeated measures ANOVA did find the interaction between stimulus type and repetition on the probability of responding "yes," $F(1, 29) = 13.4$. This demonstrates that the increase in the hit rate was larger than the increase in the false-alarm rate.

Finally, for each stimulus category, the Pearson product–moment correlation comparing each participant's priming effect and d' was calculated. There was no evidence of a correlation for words, $r = .07$, $t(28) = 0.38$, or pseudowords, $r = .04$, $t(28) = 0.20$.

Discussion

It is always unclear how we should interpret smaller priming effects for stimuli with faster baseline RTs. In this case, words were found to exhibit less priming overall than pseudowords, but their overall RT was faster as well. If we factor out baseline performance and assess priming as a percentage change in RT, words and pseudowords are indistinguishable when collapsed across test task. However, in the CID-R task, despite their higher d' (and greater possibility for enhancement of priming by recognition memory), words show a smaller priming effect than pseudowords when the baseline differences are removed, $t(29) = 2.3$. Taken together with the results of the earlier experiments, we conclude that pseudoword priming is somewhat malleable and that under some circumstances it can be larger than word priming. We should also point out that word priming itself is somewhat malleable. Priming for words can be influenced by a number of factors. Because low-frequency words demonstrate larger priming effects than high-frequency words (e.g., Ostergaard, 1998), viewing pseudowords as exceptionally low-frequency words may offer some insight into their sometimes larger priming effects.

The effect of overlap between words and pseudowords had surprisingly little effect on the priming results. Because others (e.g., Feustel et al., 1983; Rueckl, 1990) have found priming of pseudowords orthographically similar to primed words, we were concerned that the stimulus generation procedures used in prior experiments might have erroneously enhanced priming particularly of the pseudowords. However, there were no reliable differences between the high-overlap and low-overlap conditions. Although there was a trend for words to show more priming in the low-overlap condition and pseudowords to show more in the high-overlap condition (a weak prediction of a model presented later in the article), this interaction was not reliable. These results do show, however, that the stimulus generation procedure used in the prior experiments did not seriously inflate pseudoword priming.

Finally, Experiment 5 provided a clearer validation of the CID-R methodology than Experiment 4. The pattern of RTs for "new" and "old" responses is more like the pattern found in the earlier experiments and does not show the extremely fast hits that suggested contamination by recognition memory in Experiment 4. As a result, test task had no effect on priming: CID and CID-R data were indistinguishable. From this, we conclude that the addition of the recognition memory probe in the CID-R task did not qualitatively affect the results when pseudowords were included in the test list.

General Discussion of the Experiments

In this article, we have presented five experiments designed to assess repetition priming effects for words, pseudowords, and nonwords by using a task that measures the time to identify degraded stimuli. Across the experiments, several clear patterns of data emerged that enable us to address the empirical questions we set forth in the beginning of this article. First, it is apparent that there is an effect of repetition on the identification RT not only for words and pseudowords but also for nonwords designed to be as nonwordlike as possible. Although Experiment 1 showed no significant priming for nonwords, its power was relatively weak. In all other experiments using nonwords (Experiments 2, 3, and 4) significant repetition effects for nonwords were found. Further, Experiment 4 demonstrated that the repetition effect for nonwords cannot be the result of priming orthographically similar words as the nonwords were designed to have as little overlap as possible with words. Experiment 4, therefore, produced a stronger argument for nonword priming than the data of either Bowers (1994) or Hamann and Squire (1997b).

The second empirical goal of this research was to determine the relative amounts of priming for words, pseudowords, and nonwords. Specifically, we wanted to determine whether two types of ostensibly novel stimuli, pseudowords and nonwords, would show the same amount of priming. From the data, it is clear that they do not. Pseudowords (P) always showed more priming than nonwords (N; Experiments 1, 2, and 3). Interestingly, pseudoword priming appeared to be somewhat malleable and could occasionally be even larger than word (W) priming. We might therefore characterize the priming data as showing

$$\text{RepEffect (P)} \geq \text{RepEffect (W)} > \text{RepEffect (N)} > 0. \quad (1)$$

Third, using the CID-R task we have demonstrated that the priming effects found cannot be explained solely by explicit recollection of the stimulus during the implicit task. Consistently, words and pseudowords showed an effect of repetition even when participants claimed they had not seen the item in the experiment. Although less reliable overall, nonwords also showed significant repetition effects in the "new" responses in Experiment 4 and in one of the two study conditions (CID) in Experiment 3. In all other experiments, nonwords showed a nonsignificant trend toward "new" response priming.

Importantly, the recognition memory judgment was made immediately after generating the RT measure used to assess priming for each item. Recognition memory assessment was not delayed, allowing us to know that if the participant responded "new," explicit recollection of the stimulus during identification could not have had an effect on the RT. These findings show even more clearly that priming can exist for words, pseudowords, and nonwords in the absence of recognition memory. These findings are also at odds with both the logogen and acquisition models of priming as neither predicts a reliable effect for nonwords.

Modeling Repetition Priming

At this point, we turn to a presentation of a model of the mechanism for repetition priming that differs from both of the traditional accounts presented earlier. This model is based on the connectionist, or parallel distributed processing (PDP), account of repetition priming. Connectionist models have been used to provide a relatively detailed account for the mechanisms responsible for a wide range of phenomena associated with word and pseudoword reading (Plaut, McClelland, Seidenberg, & Patterson, 1996; Seidenberg & McClelland, 1989). In addition to addressing phenomena associated with adult reading performance (e.g., effects of frequency, regularity, and novelty on performance and the resulting pattern of performance following damage to the system), these models learn and have been successfully used to account for several aspects of language acquisition behavior as well. Even though it is common practice to speak of training connectionist networks to learn a task such as word reading and testing performance subsequent to training, this is usually intended as a simplification of learning in the actual cognitive system. In the connectionist framework, learning is an ongoing process as the network's weights are continually modified and fine-tuned so as to better process the information being presented (e.g., to read words presented as input more accurately). It is this ongoing modification of the mechanism responsible for processing the information that is hypothesized to be the source of the repetition priming effect (e.g., Becker, Moscovitch, Behrmann, & Joordens, 1997; McClelland & Rumelhart, 1985). That is to say, priming is the result of normal learning for recently processed information.

As with the modification or logogen account of repetition priming, priming is the result of altering or fine-tuning the same mechanism responsible for processing the stimulus. However, there are two critical differences between the PDP account and the logogen model (Morton, 1969). Unlike logogens, units in a distributed connectionist model do not represent detectors for whole words or clearly delineated parts of words. Words are represented as a distributed pattern of activity across a group of units such that similar words have similar patterns of activity. Related to this issue, there is no sense of the creation of a "new" memory in a PDP network. Knowledge in a PDP network is contained not in a discrete "store" but in the values of weights between the processing units—weights that are shared by all patterns the network processes. During learning, the network slowly adapts these weights so that it can better model the statistics of its environment. The initial presentation of a pattern results not in the creation of a new memory but in qualitatively the same learning behavior as any subsequent presentation. Repetition priming, therefore, is simply the result of this normal gradual learning that occurs as we process information. Priming is not de facto either limited to existing knowledge or the result of a separate specialized store, making the connectionist account neither a pure modification nor a pure acquisition theory (see General Discussion of the Simulations).

The MR85 Model

This account of repetition priming was explored by McClelland and Rumelhart (1985) in their distributed model of memory (MR85). This model, a relatively simple and generic associative memory network called an autoencoder, was used to demonstrate a basic repetition priming effect for stimuli analogous to words and pseudowords. It should be noted at the outset that the MR85 model was not intended to be a thorough model of long-term memory or of word perception. Rather, it is a simplified and abstract model illustrating some of the properties of a distributed, connectionist processing and learning system.

An autoencoder, such as that used by MR85, is a network that consists of a single layer of units (see Figure 3). During training on a set of items (patterns across the units), the network is given the task of arriving at a set of weights such that subsequent presentation of incomplete or degraded versions of the items results in restoration of these items to their original state. In one of the MR85 simulations, a network was trained on a set of items (taken as abstract proxies for words) that were represented in the network as a distributed pattern of activity across the single layer of units. The network's ability to process these items and distortions of these items (taken as abstract proxies for pseudowords) was measured in terms of the strength of the units' activation over time (updates of the activation in the entire network). McClelland and Rumelhart (1985) found that not only would the network show facilitation in processing items it had been trained on but it would also show a similar (though somewhat lesser) facilitation for distortions of these items. This property, known as generalization, arises from the fact that unlike the traditional logogen model (Morton, 1969) items are represented not as single units but as a distributed pattern of activity across an entire layer of processing units. Though the distorted items had never been exposed to the network, by being similar to trained items, the knowledge the network had gained during training could aid in processing these items.

In addition to this basic finding, McClelland and Rumelhart (1985) demonstrated that recent exposure to familiar items and

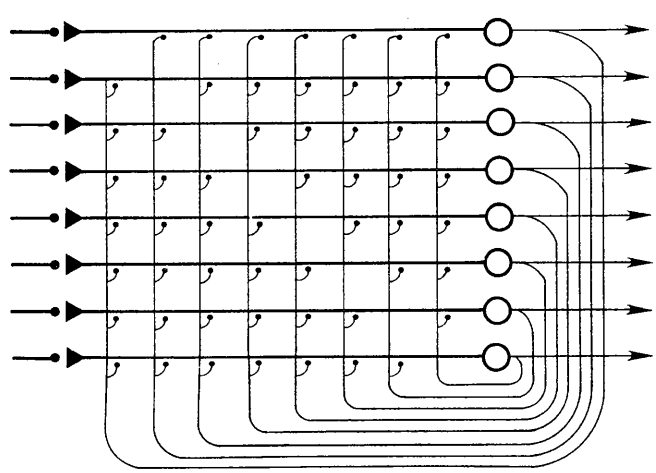

Figure 3. The abstract distributed-processing model used by McClelland and Rumelhart (1985) and reused here in simulations of priming effects. External inputs are represented by the inputs arriving at the extreme left. Internal inputs arise through the connections from other units. From "Distributed Memory and the Representation of General and Specific Information," by J. McClelland and D. Rumelhart, 1985, *Journal of Experimental Psychology: General, 114,* p. 162. Copyright 1985 by the American Psychological Association. Reprinted with permission.

their distortions resulted in subsequent faster processing. By engaging the learning process in the network whenever the network processes an item, the weights in the network are modified such that it will better process that item in the future. This arises from the normal learning process that occurs in this and many other connectionist networks.

Given the basic success and relative simplicity of the MR85 model, we opted to use it as a starting point for our exploration of the details of priming in connectionist models. Except where noted, all parameters from the MR85 model were used here. Although the model as initially formulated by McClelland and Rumelhart (1985) does exhibit priming effects, we found in preliminary studies that the particular form of the learning rule used by McClelland and Rumelhart leads the model to provide a particularly poor fit to the empirical data on repetition priming for previously unfamiliar items. Because of this we present two versions of the model: one using the error-correcting learning rule used by MR85 and one using a simple version of a Hebbian, or correlational, learning rule.

Architecture and Processing in the MR85 Model

The MR85 model has only one layer of units that are fully interconnected (Figure 3). In addition to this internal input, each unit may also receive external input. Presenting an item to the network consists of creating a pattern of such external inputs, having a value (typically either 1 or -1) for the input to each of the units in the network.

When an input is presented to the network, an iterative settling process begins. Within each cycle of this settling process, all of the units in the network are updated. For each update, the constraints imposed by any external input to each unit and the constraints imposed by the activations of connected units together determine whether the unit will be more or less active on the next timestep. The net input to each unit in the MR85 model is

$$net_i(t) = E(ext_i) + I[int_i(t)], \tag{2}$$

where E and I are constants that weight the effect of input impinging on unit i from external (*ext*) and internal (*int*) influences, respectively. The term int_i is the sum of inputs from all units other than unit i itself:

$$int_i(t) = \sum_{j \neq i} a_j(t) w_{ij}. \tag{3}$$

In cases where the net input is positive, the new activation of the unit at time $t + 1$ becomes

$$a_i(t + 1) = [1 - a_i(t)]net_i(t) - Da_i. \tag{4}$$

When the net input is not positive, the new activation becomes

$$a_i(t + 1) = [a_i(t) - (-1)]net_i(t) - Da_i. \tag{5}$$

The factor in parentheses represents the distance between the current activation and its maximum (1) or minimum (-1) value. Excitatory (positive) net input pushes the activation toward the maximum, and inhibitory (negative) net input pushes the activation toward the minimum. In both cases, there is a restoring force or decay that tends to pull the activation back toward 0. The magnitude of this restoring force is determined by the constant D.

Given a fixed pattern of external input presented at time $t = 0$, the network eventually settles into a fixed state as all units reach asymptotic activation values. To relate the model to RT data, we assume a response is initiated when the overall strength of activation reaches a criterion value, as discussed further below.

Two Forms of Learning

The delta rule. Learning in the model occurs after settling by adjusting the weights. MR85 used a simple error-correcting learning rule known as the delta rule to make these adjustments. The delta rule adjusts the weights to minimize the difference between each unit's external input from the environment and its internal input from the rest of the network. The change in the weight to unit i from unit j is given by

$$\Delta w_{ij} = \eta \delta_i a_j, \tag{6}$$

where η is a learning rate constant and δ represents this difference ($ext_i - int_i$). With repeated presentation of the training set, a delta-rule network can learn any linearly separable set of patterns.

The Hebb rule. A different approach to learning a set of weights to produce a desired mapping can be found in associative learning algorithms. The simplest of these algorithms is the Hebb rule (Hebb, 1949), in which learning is proportional to the coproduct of two connected units' activations:

$$\Delta w_{ij} = \eta a_i a_j. \tag{7}$$

The Hebb rule is attractive not only because of its simplicity but also because of a clear parallel between it and a synaptic modification rule found in electrophysiological experiments on a phenomenon that may be the biological mechanism of learning, namely, long-term potentiation (e.g., Bear & Malenka, 1994).

Simulation Methodology

Patterns. Three sets of 64-bit patterns were constructed to correspond to the words, pseudowords, and nonwords used in the experiments. The groups of patterns are labeled familiar (FAM), novel consistent (NC), and novel inconsistent (NI) and correspond to (a) patterns each network is trained on, (b) patterns derived from trained patterns, and (c) truly novel patterns. To create this structure, a full complement of 32-bit orthogonal ± 1 vectors was generated with half of these vectors allocated to generating the FAM and NC vectors and the other half allocated to generating the NI vectors. The FAM vectors were generated by abutting each of the sixteen 32-bit vectors with the next vector on the list. The NC vectors were generated from the same set, abutting each vector with the second one after it. Finally, the NI vectors were created by using the same procedure as the FAM vectors but operating on the other set of sixteen orthogonal vectors. The result is a set of three lists of sixteen 64-bit vectors such that the FAM and NI are all orthogonal to each other and the NC overlap with the FAM and are spanned by the space generated by the FAM vectors. As such, the NC items (pseudowords) are similar to and share the structure of the FAM items (words), whereas the NI items (nonwords) are as dissimilar to the FAM items as possible.

Pretraining and priming. The networks were pretrained on all 16 FAM vectors, serving as a proxy for our experimental participants' existing knowledge of words. Training continued

Table 5
Network Settling Times

	Settling times to List A				Settling times to List B	
Learning rule	Unprimed[a]	Primed[b]	Priming A baseline	Priming B baseline	Unprimed[a]	Primed[b]
Delta						
FAM	119	121	−2	2	118	123
NC	202	192	10	5	202	207
NI	308	286	22	6	308	314
Hebb						
FAM	108	97	11	14	108	111
NC	196	182	14	17	196	199
NI	312	310	2	6	312	316

Note. FAM = familiar; NC = novel consistent; NI = novel inconsistent.
[a] Number of cycles required for the network to settle after training on all the FAM items. [b] Number of cycles required for the trained network to settle after one additional epoch of training on the A sublist of FAM, NC, and NI items.

until performance reached a criterion that represented good performance with moderate room for improvement (specifically, an average sum-squared error of 0.01 per unit per pattern, which corresponded to an average normalized dot product between the network's output and the target output of .78). During training, equal weight was given to the external and internal constraints on activation ($E = I = 0.1$; $D = 0.05$), and the network was allowed to settle for 20 cycles on each pattern. Once trained, each network's performance was assessed, and the networks were "primed" by further training on a subset of patterns. The "primed" performance was then assessed for both the primed and unprimed items. The amount of priming, therefore, can be taken as the difference in performance either between the primed and unprimed items or between the pre- and postpriming measures of primed items.

Performance assessment. To assess each network's performance, we used a version of the normal settling procedure modified both to increase resolution in our measure (by increasing settling time) and to more closely parallel the experimental paradigm. The internal strength parameter, I, was reduced to 0.05, and the external strength parameter, E, began at 0 and increased linearly with increments of 0.0002 per cycle. In this way, the external input to the network is initially weak but grows to eventually dominate the activation over time.

The networks were said to have settled (or made a response) when the strength of activation as measured by the normalized vector length was greater than 0.5. (The normalized vector length is the square root of the sum of the squares of the activations of the units, divided by the square root of the number of units.) Priming was measured as a decrease in the number of cycles required to cross this threshold.

Simulation Results

Delta-rule simulations. After training on all the FAM patterns, the network trained with the delta rule was tested on two sets of mixed stimulus lists, A and B (Table 5). The A list consisted of half of the FAM items used in training, the NC items generated from these items,[5] and half of the NI items. The B list consisted of the remaining eight patterns in each category. Settling times for these items are presented in the "Unprimed" columns of Table 5. For reference, the untrained network's settling time is approximately 260 cycles for all stimulus types.

Consistent with the empirical data, FAM items are processed most rapidly (119 cycles), followed by NC items (202 cycles), and finally by NI items (308 cycles). The network's weights have been trained on the FAM items, resulting in full cooperation between the external and internal influences on activation and a rapid settling time. Because the NC items share a portion of this structure, they derive some benefit from the weights in their settling time. Being wholly unrelated to the FAM items, the NI items not only derive no benefit from but are even interfered with by the internal weights, resulting in a slow settling time.

After one presentation of each item (one epoch of priming) on the A list, performance was again assessed for the A and B lists. Recall that the priming effect can be assessed as the difference between the settling time for the A list after the priming manipulation and either the settling time on the same item prior to any priming manipulation or the postmanipulation settling time for the unprimed B-list items. Using the former baseline, FAM items showed a 2-cycle negative effect, NC items a 10-cycle positive effect, and NI items a 22-cycle positive effect. Using the latter baseline (a closer parallel to the empirical methodology) the results are qualitatively similar, though the effect for FAM items is no longer negative. As we increase the number of epochs of priming to three and five (see Table 6), the effects are magnified. Clearly, the model produces a particularly poor fit to the empirical data. Priming effects for familiar items (i.e., words) are massively underpredicted, and effects for NI items (i.e., nonwords) are massively overpredicted.

One important source of the poor priming predictions can be found in the equation for the delta learning rule itself (Equation 6). The change in a weight between two units is proportional to the

[5] Alternatively, one could use the NC items generated from the FAM items not included on the priming list. Doing so results in slightly less NC priming as weight changes made by the FAM items provide less support for the less similar NC items. As with the results of Experiment 5, this effect of cross-stimulus-type priming is not very large.

Table 6
Effects of Number of Epochs and Stimulus List on Primed Settling Times

	1:A[a]	3:A	5:A	3:FAM	3:NI
Delta					
FAM	119	123	124	114	128
NC	202	174	160	199	212
NI	308	244	208	309	238
Hebb					
FAM	108	79	67	83	109
NC	196	154	119	178	198
NI	312	304	298	317	295

Note. A = List A; FAM = familiar; NI = novel inconsistent; NC = novel consistent.
[a] One additional epoch of training on List A corresponded to the standard priming protocol. See Table 5.

difference between the internal and external constraints on the receiving unit's activation (δ). Items present during training (FAM) produce small error scores and result in only minor modifications to the weights. NI items, however, result in large error scores and subsequent large changes to the weights. As a result, priming for NI items is significantly greater than priming for FAM items.

Note that because the same weights are being used to encode the entire environment, the large weight changes induced by the NI items during priming can have a deleterious effect on FAM items, overshadowing the minor facilitation generated by priming these items. The 3:FAM column of Table 6 shows some facilitation for FAM items after three epochs of priming on these items alone. In contrast, the 3:NI column shows interference for the FAM items and large amounts of facilitation for the NI items after three epochs of priming on these NI items.

Hebb rule simulations. The network trained and primed with the Hebb rule presents a strikingly different pattern of results and produces a very good qualitative fit to the empirical data. Like the delta-rule network, when examining the overall settling time, the weights derived by the Hebb rule produce an effect of consistency with the training set (Table 5). FAM items (108 cycles) are processed faster than NC items (196 cycles), which are faster than NI items (312 cycles). Unlike the delta rule, the Hebb rule produces a sizable priming effect for FAM items (11 cycles), a large effect for NC items (14 cycles), and a very small effect for NI items (2 cycles) after one epoch using the prepriming results as a baseline. Similar results are found using the alternate baseline.

The source of the priming predictions can again be found in the learning rule. In the Hebb rule (Equation 7), weights are modified in proportion to the coproduct of the activations of units. Essentially, the Hebb rule will make changes to the weights in proportion to the square of the strength of activation of units in the network. The strength of the network's response as measured by the normalized length of the activation vector after training is .79 for FAM items, .69 for NC items, and .57 for NI items. Weight changes, therefore, are almost twice as large for FAM items as for NI items.

Although the original intent of the model was to explore the relative amounts of priming, the qualitative fit was good enough to warrant an elementary quantitative analysis. The overall settling times in the network were fitted to the raw RTs for words, pseudowords, and nonwords from Experiment 1 via a least-squares linear fit, RT = cycles $\times$ 4.55 + 2,088. The model fitted the raw

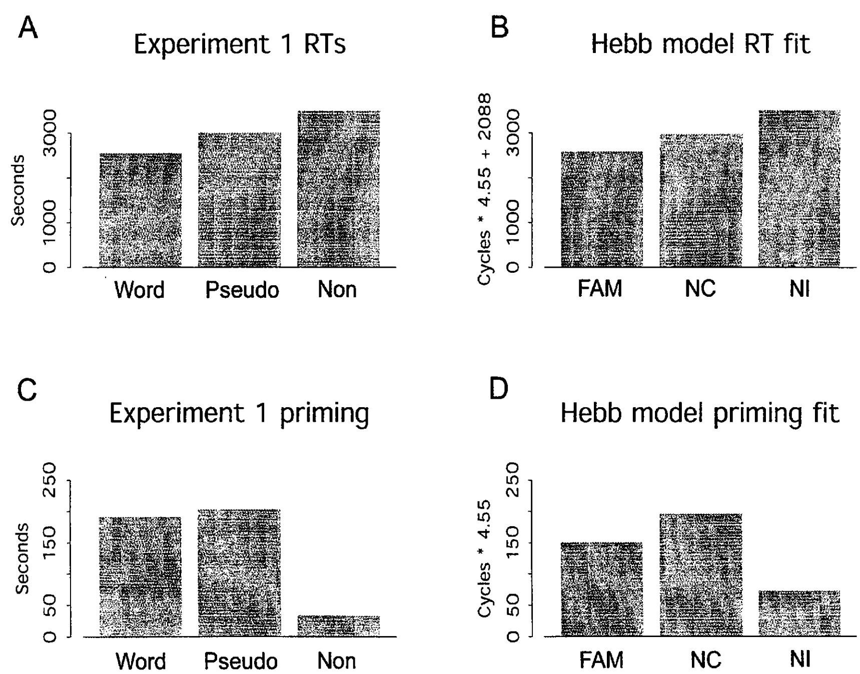

Figure 4. (A) Reaction times (RTs) to words, pseudowords, and nonwords from Experiment 1; (B) fitted Hebb model RTs; (C) priming effects in Experiment 1; and (D) fitted Hebb model priming effects. Pseudo = pseudoword; Non = nonword; FAM = familiar; NC = novel consistent; NI = novel inconsistent.

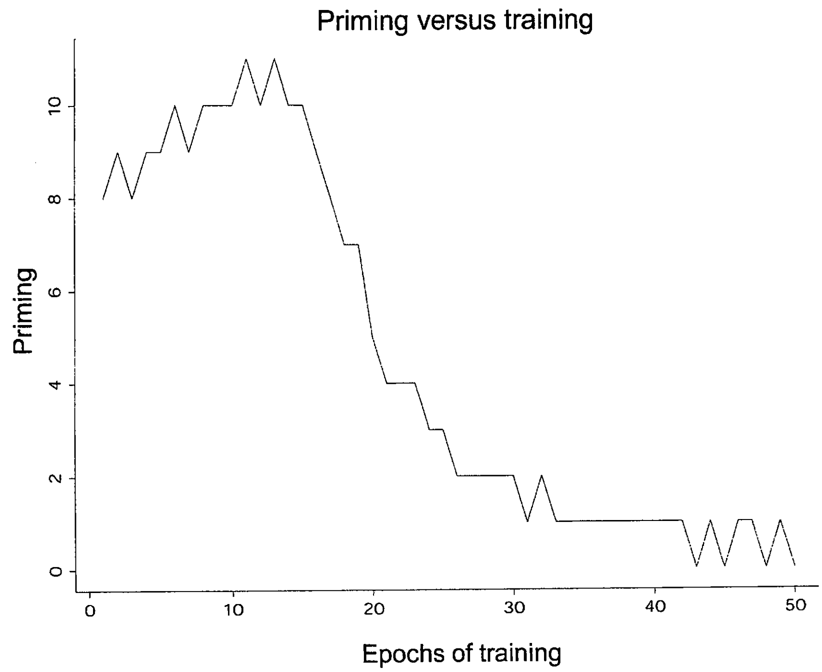

Figure 5. Priming effect versus amount of training with the Hebb rule. The difference in settling time between successive trials is plotted against the number of trials of training on a single pattern. As overall performance increases as a result of training, the magnitude of the priming effect is compressed. The overall excellent performance on familiar items can therefore compress the effect of repetition on these items.

RTs in the data exceptionally well (see Figures 4A and 4B) with a resulting correlation of .998, $t(1) = 14.2, p < .05$. When this same transformation was applied to the priming effects, the model's predicted magnitudes were smaller than the actual effects for all three stimulus types (50, 64, and 9 ms). As the magnitude of priming is directly related to the size of the learning rate constant and as this was initially set to a relatively arbitrary value (0.005), we increased the value of this constant to 0.015 so that a single exposure to each item would produce larger weight changes and more priming. With only this modification, the model's predicted priming is increased overall and produces a reasonable quantitative fit ($r = .95$) to the observed priming effects (see Figures 4C and 4D).

It should be noted that there is a ceiling effect operating on the settling performance of the network that reduces the observed priming effect for FAM items. Although weight changes for these items are higher than for NC items, the benefit of weight changes on settling time is reduced with increased performance. This effect is demonstrated in Figure 5, in which the difference in settling time between successive trials is plotted against the number of trials of training on a single pattern. As we can see, the nonlinear settling behavior compresses the priming effect as overall performance increases. The overall excellent performance on FAM items can therefore compress the effect of repetition on these items. This lends some support to the hypothesis that the weakened priming of words in Experiment 3 was the result of the significantly faster RTs found in that experiment and gives one explanation for the relatively large pseudoword priming effects.

General Discussion of the Simulations

Although these simulations demonstrate that a PDP model can provide a basic fit to the empirical data, more important, an understanding of the roots of their behavior raises a number of theoretical issues that warrant discussion. First, one of the central features of the model is that knowledge is acquired through the adaptation of connection weights in a distributed network. All knowledge in the network and processing of information by the network is embodied in the set of connection weights. This aspect of the model not only blurs the distinction between memory and information processing but it goes further to provide an alternative to the notion that the process of priming must either strengthen an existing memory trace or create a new one that did not exist before. It replaces these two separate notions with the idea that priming, or the facilitation of performance on an item by its prior presentation, occurs without requiring the existence of disembodied memories. Rather, it simply reflects the effects of alterations of the connection weights that participate in the act of information processing. As such, this aspect of the PDP framework distinguishes it from the majority of theories of priming, including the logogen/modification and acquisition theories of implicit memory presented earlier, and provides us with a well-specified alternate mechanism (e.g., Becker et al., 1997; McClelland & Rumelhart, 1985).

The computational nature of the PDP framework allows us to explore the ramifications of a range of possible implementations of this weight-adaptation mechanism. The first simulation used the error-correcting delta rule as the method of adapting the weights in the network. This resulted in a severe overprediction of nonword (NI) priming and underprediction of word (FAM) priming, the source of which we hypothesized to be the error-driven nature of learning in the delta rule. By the very nature of the learning rule, larger errors in performance result in larger weight changes.

It should be noted that the overpredicting of nonword priming is not limited to the MR85 model or to the particular variants of the error-driven algorithm presented here. Stark (1997) has demonstrated that the same basic findings arise using several variants on error-correcting learning rules (delta rule, backpropagation, recurrent backpropagation, deterministic Boltzmann, and contrastive Hebbian learning) and a host of architectures and tasks (e.g., three-layer encoder networks using 0/1 or ± 1 units, two-layer autoencoders, three-layer pattern associators, the Seidenberg and McClelland [1989] model of word identification, and "deep" pattern associators that force weight error derivatives through several layers). Numerous attempts to modify the basic activation or learning rules while maintaining error-driven learning similarly met with an overwhelming failure to significantly reduce nonword priming. The only model that used an error-driven learning rule and demonstrated larger priming effects for words and pseudowords than for nonwords was a network in which the error signal was derived from the output signal of a separate network trained in parallel with the network producing the behavior. Although this network used error-driven learning, the learning that occurred was based on how well a separate network processed the input pattern, resulting in learning that is proportional to how consistent the input pattern is with the network's existing knowledge (much like learning in the Hebb network).[6]

From this finding, we conclude that learning rules that update weights based on the difference between current behavior and ideal behavior are not appropriate in models of implicit memory. Even with significant modifications, networks that use this learning principle grossly violate the pattern of repetition priming effects presented here. As an alternative, we suggest that the learning that occurs in implicit memory is primarily based on the strengthening of connections between the units in the distributed pattern of activity that arises during performance of some task and that the degree of strengthening is proportional to the coproduct of the activation between units. A result of this mechanism is that implicit memory will exist to the extent that the system can already perform some task, execute some behavior, or process some piece of information.

Given that a great deal of connectionist modeling work, particularly in the area of word reading (e.g., Plaut et al., 1996; Seidenberg & McClelland, 1989; Sejnowski & Rosenberg, 1987), relies on error-driven learning rules (specifically, backpropagation) it is useful to consider how to relate our results to these models of the word-reading process. One step we would not want to take would be to suggest that perhaps priming occurs via Hebbian learning, whereas acquisition of reading skill occurs through backpropagation. Indeed, we specifically eschew this proposal: It is our view that priming reflects the very same connection adjustment process that gives rise to fluent reading ability, so that ultimately the learning rule used for both acquisition and priming will have to be unified.

One possibility is that the unification might occur through finding a way of accounting for our present data in models that rely on an error-correcting learning rule. This might seem like the only possible resolution of the conflict between reading models and our priming results, because it is often assumed that models relying on Hebbian learning cannot train multilayer networks adequately to deal with as complex a task as word reading or, in general, to deal with any challenging information-processing task. As reviewed above, we extensively explored the possibility of accommodating our findings in an error-correcting framework and failed to find an architecture that addresses our findings, but we cannot rule out this possibility. Indeed, it has been suggested (D. Plaut, personal communication, 1997) that the magnitude of backpropagated error signals can be strongly attenuated when processing unfamiliar items, just as activations are attenuated under such circumstances, and we very much expected to find such effects in some of our multilayer simulations. On the basis of this, we are not in a position to rule out the possibility that further research will lead to an adequate architecture that captures our priming effect.

Alternatively, it may be that a way will be found to account for the acquisition of word-reading skill within a Hebbian or Hebb-like learning framework. There are a large number of models now in existence in which several layers of an information-processing system are thought of as arising through the use of unsupervised learning procedures such as competitive learning (Grossberg, 1976; Rumelhart & Zipser, 1985; Von der Malsberg, 1973) or even a relatively straightforward implementation of Hebbian learning coupled with some form of weight normalization or limitation at some maximum or minimum value (e.g., Linsker, 1986a, 1986b). Such procedures have often been criticized because it is unclear how they can adapt the learning process to be sensitive to the goals of learning. However, there are several ways in which this can be done. We mention two: First, the inputs to a competitive layer of units might come both from the input and from the desired output (which may be present at least some of the time in conjunction with an input, as when a child sees her mother point to a word and at the same time read the word aloud). In that case, as Rumelhart and Zipser (1985) showed, the learning is Hebbian, but the "desired output," now just an element of the input, strongly conditions the learning and organizes it in a way that, in simple cases at least, leads to acquisition of the ability to produce the desired output in response to the input. Second, Hebbian learning may be modulated by a reinforcement signal (see Barto, 1992). As Mazzoni, Andersen, and Jordan (1991) have shown, this can lead to acquisition of a difficult multilayer learning problem, albeit somewhat more slowly than would occur through the use of an error-correcting learning rule. It is unclear how to construe what might be the reinforcement signal in our task; one possibility is that a reinforcement signal occurs whenever a letter string is successfully read. In that case, reinforcement would be equivalent for all types of items (because, in our paradigm, all are read correctly during the acquisition phase of the experiment). Thus, the reinforcement effect would disappear into the fixed learning rate constant, and differences between items would reflect the remaining Hebbian component of learning. We note that there may be other ways in which a Hebbian procedure can lead to successful learning of a complex task in a multilayer network.

[6] Priming in the network that had an error signal that was derived from the correct output (the "Teacher network") was, of course, larger for nonwords than words or pseudowords.

A final possibility might be that the brain relies on a hybrid learning algorithm such as LEABRA (O'Reilly, 1996), in which Hebbian learning and error-correcting learning are used in combination, with each weight change having both a Hebbian and an error-correcting component (these are simply added together to determine the overall magnitude of the weight change). It may be that there would be a choice of the relative amount of error-correcting versus Hebbian learning that would lead both to successful acquisition of reading in a multilayer network and to a successful account of our priming effects.

In addition to the data presented here, several studies concerning amnesic learning provide some motivation for considering the possibility that the brain may rely on some form of Hebbian learning. Glisky and colleagues (Glisky & Schacter, 1987, 1988, 1989; Glisky, Schacter, & Tulving, 1986) attempted to teach amnesic patients a complex data entry task and elementary computer-programming skills. The tasks chosen usually rely heavily on the "declarative" or "explicit" memory that amnesic patients profoundly lack (e.g., Graf & Schacter, 1985; Squire, 1992). They found that despite their serious impairment using traditional study and test paradigms, the patients could gradually learn the complex tasks if the study phase used a technique they called the "method of vanishing cues." This technique involves starting training by presenting the patient with a situation in which a response is to be given and providing the patient with the correct response. As the patient practices the task, the input specifying the correct response is gradually eliminated (e.g., by deleting letters from the correct response if it is a word). A key feature of this method is that it virtually guarantees correct performance on each trial as the participant is asked to provide more of the answer over multiple trials, and thus allows the patient to rely on Hebbian learning.

Recent work by Wilson and her colleagues (Baddeley & Wilson, 1994; Wilson, Baddeley, & Evans, 1994; Wilson & Evans, 1996) explored this idea in more depth by examining the effect of errors made during study on the performance of amnesic patients in a list-learning task. In the "errorful" task, amnesic patients and controls were given word stems and asked to guess the target word. The stems had multiple valid completions, making errors probable.[7] After the target was guessed, three incorrect guesses had been made, or 15 s had elapsed, the experimenter revealed the target item and instructed the participant to write it on a piece of paper. In the "errorless" task, participants were given the stem, immediately informed of the target, and asked to write down the target. Controls and amnesics ran through a list of words three times before entering the cued-recall test phase. The study and test block was run a total of three times for each participant using the same list each time. Although amnesic patients were impaired in both tasks when compared with either young or elderly controls, there was a large effect of study task on cued-recall test performance for the amnesic population (smaller effects existed for the two control groups). Participants who were not allowed to make errors during study were significantly more accurate in their cued-recall performance than participants who were allowed to test their knowledge by guessing. If we assume that the amnesic patients were relying on implicit memory to perform this task (a hypothesis supported by a detailed analysis of the error data), these data are consistent with our claim that implicit memory acts by strengthening whatever pattern of activity arises during processing. The generation of incorrect responses strengthens these responses and induces weight changes inconsistent with the target pattern. If these incorrect patterns of activity are prevented from existing, the correct weight changes can accrue over multiple presentations. Note that this finding is in direct contrast to the error-driven learning paradigm of the delta rule and other supervised PDP algorithms.

Finally, we note that McClelland (in press) has recently suggested that a Hebbian learning rule may help explain aspects of critical period effects in language acquisition. Consider the finding that it is difficult for Japanese adults to learn the distinction between the English phonemes /r/ and /l/. In Japanese, there is only one phoneme (usually written with an /r/), and it is possible that the mechanisms of perception in Japanese adults have been adapted through perceptual learning to treat all inputs in the range of English /r/ and /l/ sounds as examples of this Japanese phoneme. In connectionist terms, this means that all such inputs evoke the same pattern of activation, corresponding to the percept of that phoneme. If synaptic modification in the brain is Hebbian, any occurrence of either an /r/ or an /l/ would evoke this perception, and so would result in the reinforcement of the tendency to produce this percept. Thus, paradoxically, Hebbian learning may tend to reinforce language perception habits that have been established in one language context but may not be optimal in another. McClelland reported simulations illustrating how this process may work in a simulation model and preliminary experimental results indicating support for predictions arising from this model for the relative efficacy of different methods of training Japanese adults to discriminate between /r/ and /l/.

The foregoing discussion suggests that connectionist models may provide a fertile framework for further explorations of the mechanisms underlying repetition priming effects. Different versions of such models lead to starkly divergent predictions for the pattern of results that might have occurred in our experiments and indicate an important challenge to existing models of word reading based on error correction. We hope that the attempt to reconcile such models with our data will lead to a deeper understanding of the mechanisms of implicit learning.

Conclusions

We have presented data from five experimental studies showing repetition priming effects for words, pseudowords, and highly nonwordlike nonwords. We have shown that although nonwords can demonstrate an effect of repetition, the magnitude of this effect is smaller than that for words or pseudowords. Further, by using the CID-R testing methodology, we have shown that the repetition effect exists even if participants fail to recognize the item at the time of the identification test and that recognition memory performance and priming effects are not strongly correlated.

In addition, we have proposed a computational model of repetition priming based on an earlier PDP account. Using a simple Hebbian network, we produced a qualitative fit to the central pattern of results from the experimental data and showed how consistency with current knowledge, rather than novelty, can affect

[7] In the "errorful" condition, at least one error was guaranteed. If the participant guessed the actual target on the first trial, an alternate target word was used for that trial.

both the speed of processing and the amount of priming. Further, we proposed that like the Hebbian model, the mechanism of implicit memory is such that it strengthens the connections between units in a distributed pattern of activity that results from whatever processing actually occurs. Although this model is not intended as a comprehensive model of implicit memory, we believe that the principles of learning distributed representations of memories that it embodies provides the groundwork for further exploration.

References

Anderson, J. R. (1993). *Rules of the mind.* Hillsdale, NJ: Erlbaum.

Baddeley, A., & Wilson, B. (1994). When implicit learning fails: Amnesia and the problem of error elimination. *Neuropsychologia, 32,* 53–68.

Barto, A. G. (1992). Reinforcement learning and adaptive critic methods. In D. A. White & D. A. Sofge (Eds.), *Handbook of intelligent control: Neural, fuzzy, and adaptive approaches* (pp. 469–491). New York: Van Nostrand Reinhold.

Bear, M. F., & Malenka, R. C. (1994). Synaptic plasticity: LTP and LTD. *Current Opinion in Neurobiology, 4,* 389–399.

Becker, S., Moscovitch, M., Behrmann, M., & Joordens, S. (1997). Long-term semantic priming: A computational account and empirical evidence. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 23,* 1059–1082.

Bowers, J. (1994). Does implicit memory extend to legal and illegal nonwords? *Journal of Experimental Psychology: Learning, Memory, and Cognition, 20,* 534–549.

Bowers, J., & Schacter, D. (1990). Implicit memory and test awareness. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16,* 404–416.

Bowers, J., & Schacter, D. (1993). Priming of novel information in amnesic patients: Issues and data. In P. Graf & M. Masson (Eds.), *Implicit memory: New directions in cognition, development, and neuropsychology* (pp. 303–326). Hillsdale, NJ: Erlbaum.

Brown, A., & Mitchell, D. (1994). A reevaluation of semantic versus nonsemantic processing in implicit memory. *Memory & Cognition, 22,* 533–541.

Cermak, L., Talbot, N., Chandler, K., & Wolbarst, L. (1985). The perceptual priming phenomenon in amnesia. *Neuropsychologia, 23,* 615–622.

Challice, B., & Brodbeck, D. (1992). Level of processing affects priming in word fragment completion. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 18,* 595–607.

Cohen, J., MacWhinney, B., Flatt, M., & Provost, J. (1993). PsyScope: A new graphic interactive environment for designing psychology experiments. *Behavioral Research Methods, Instruments & Computers, 25,* 257–271.

Cohen, N., & Squire, L. (1980, October). Preserved learning and retention of pattern analyzing skill in amnesia: Dissociation of knowing how and knowing that. *Science, 21,* 207–209.

Coltheart, M. (1981). The MRC psycholinguistic database. *Quarterly Journal of Experimental Psychology, 33,* 497–505.

Corkin, S. (1968). Acquisition of motor skill after bilateral medial temporal excision. *Neuropsychologia, 6,* 255–265.

Diamond, R., & Rozin, P. (1984). Activation of existing memories in the amnesic syndrome. *Journal of Abnormal Psychology, 93,* 98–105.

Dorfman, J. (1994). Sublexical components in implicit memory for novel words. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 20,* 1108–1125.

Eichenbaum, H. (1992). The hippocampal system and declarative memory in animals. *Journal of Cognitive Neuroscience, 4,* 217–231.

Feustel, T. C., Shiffrin, R. M., & Salasoo, A. (1983). Episodic and lexical contributions to the repetition effect in word identification. *Journal of Experimental Psychology: General, 112,* 309–346.

Glanzer, M., & Adams, J. K. (1985). The mirror effect in recognition memory. *Memory & Cognition, 13,* 8–20.

Glanzer, M., & Adams, J. K. (1990). The mirror effect in recognition memory: Data and theory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16,* 5–16.

Glanzer, M., Adams, J. K., Iverson, G. J., & Kiosk, K. (1993). The regularities of recognition memory. *Psychological Review, 100,* 546–567.

Glisky, E., & Schacter, D. (1987). Acquisition of domain-specific knowledge in organic amnesia: Training for computer-related work. *Neuropsychologia, 25,* 893–906.

Glisky, E., & Schacter, D. (1988). Long-term retention of computer learning by patients with memory disorders. *Neuropsychologia, 26,* 173–178.

Glisky, E., & Schacter, D. (1989). Extending the limits of complex learning in organic amnesia: Computer training in a vocational domain. *Neuropsychologia, 27,* 107–120.

Glisky, E., Schacter, D., & Tulving, E. (1986). Computer learning by memory-impaired patients: Acquisition and retention of complex knowledge. *Neuropsychologia, 24,* 313–328.

Graf, P., & Mandler, G. (1984). Activation makes words more accessible, but not necessarily more retrievable. *Journal of Verbal Learning and Verbal Behavior, 23,* 553–568.

Graf, P., Mandler, G., & Haden, P. E. (1982, December). Simulating amnesic symptoms in normal subjects. *Science, 218,* 1243–1244.

Graf, P., & Schacter, D. (1985). Implicit and explicit memory for new associations in normal and amnesic subjects. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 11,* 501–518.

Graf, P., Shimamura, A., & Squire, L. (1985). Priming across modalities and across category levels: Extending the domain of preserved function in amnesia. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 11,* 386–396.

Grossberg, S. (1976). On the development of feature detectors in the visual cortex with applications to learning and reaction-diffusion systems. *Biological Cybernetics, 21,* 145–159.

Hamann, S., & Squire, L. (1996). Level-of-processing effects in word-completion priming: A neuropsychological approach. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 22,* 933–947.

Hamann, S., & Squire, L. (1997a). Intact perceptual memory in the absence of conscious memory. *Behavioral Neuroscience, 111,* 850–854.

Hamann, S., & Squire, L. (1997b). Intact priming for novel perceptual representations in amnesia. *Journal of Cognitive Neuroscience, 9,* 699–713.

Hayman, C., & Tulving, E. (1989). Contingent dissociation between recognition and fragment completion: The method of triangulation. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 15,* 941–956.

Hebb, D. O. (1949). *The organization of behavior.* New York: Wiley.

Jacoby, L. (1991). A process dissociation framework: Separating automatic and intentional uses of memory. *Journal of Memory and Language, 30,* 513–541.

Jacoby, L., & Dallas, M. (1981). On the relationship between autobiographical memory and perceptual learning. *Journal of Experimental Psychology: General, 110,* 306–340.

Jacoby, L., & Witherspoon, D. (1982). Remembering without awareness. *Canadian Journal of Psychology, 36,* 300–342.

Kučera, H., & Francis, W. N. (1967). *Computational analysis of present-day American English.* Providence, RI: Brown University Press.

Light, L., Singh, A., & Crapps, J. (1984). The dissociation of memory and awareness in young and older adults. *Journal of Clinical and Experimental Neuropsychology, 8,* 62–74.

Linsker, R. (1986a). From basic network principles to neural architecture: I. Emergence of spatial-opponent cells. *Proceedings of the National Academy of Sciences USA, 83,* 7508–7512.

Linsker, R. (1986b). From basic network principles to neural architecture:

II. Emergence of orientation-selective cells. *Proceedings of the National Academy of Sciences USA, 83,* 8390–8394.

Marsolek, C., Kosslyn, S., & Squire, L. (1992). Form-specific visual priming in the right cerebral hemisphere. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 18,* 492–508.

Mazzoni, P., Andersen, R. A., & Jordan, M. I. (1991). A more biologically plausible learning rule for neural networks. *Proceedings of the National Academy of Sciences USA, 88,* 4433–4437.

McClelland, J. L. (in press). Failures to learn and their remediation: A competitive, Hebbian, approach. In J. L. McClelland & R. S. Siegler (Eds.), *Mechanisms of cognitive development: Behavioral and neural perspectives.* Hillsdale, NJ: Erlbaum.

McClelland, J., McNaughton, B., & O'Reilly, R. (1995). Why are there complementary learning systems in the hippocampus and neocortex: Insights from the successes and failures of connectionist models of learning and memory. *Psychological Review, 102,* 419–457.

McClelland, J., & Rumelhart, D. (1985). Distributed memory and the representation of general and specific information. *Journal of Experimental Psychology: General, 114,* 159–188.

Milner, B. (1962). Les troubles de la memoire accompagnant des lesions hippocampiques bilaterals [Memory impairment associated with bilateral hippocampal lesions]. In P. Passouant (Ed.), *Physiologie de l'hippocampe* (pp. 257–272). Paris: Centre National de la Recherche Scientifique.

Morton, J. (1969). The interaction of information in word recognition. *Psychological Review, 76,* 165–178.

O'Reilly, R. C. (1996). Biologically plausible error-driven learning using local activation differences: The generalized recirculation algorithm. *Neural Computation, 8,* 895–938.

Ostergaard, A. L. (1998). The effects on priming of word frequency, number of repetitions, and delay depend on the magnitude of priming. *Memory & Cognition, 26,* 40–60.

Plaut, D. C., McClelland, J. L., Seidenberg, M. S., & Patterson, K. E. (1996). Understanding normal and impaired word reading: Computational principles in quasi-regular domains. *Psychological Review, 103,* 56–115.

Ratcliff, R., & McKoon, G. (1995). Bias in the priming of object decisions. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21,* 754–767.

Roediger, H., & McDermott, K. (1993). Implicit memory in normal human subjects. In H. Spinnler & F. Boller (Eds.), *Handbook of neuropsychology* (Vol. 8, pp. 63–131). Amsterdam: Elsevier.

Rueckl, J. (1990). Similarity effects in word and pseudoword repetition priming. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16,* 374–391.

Rueckl, J., & Olds, E. (1993). When pseudowords acquire meaning: The effect of semantic associations on pseudoword repetition priming. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 19,* 515–527.

Rumelhart, D. E., & Zipser, D. (1985). Feature discovery by competitive learning. *Cognitive Science, 9,* 75–112.

Salasoo, A., Shiffrin, R. M., & Feustel, T. C. (1985). Building permanent memory codes: Codification and repetition effects in word identification. *Journal of Experimental Psychology: General, 114,* 50–77.

Schacter, D. (1990). Perceptual representation systems and implicit memory: Toward a resolution of the multiple memory systems debate. In A. Diamond (Ed.), *Annals of the New York Academy of Sciences: Vol. 608. The development and neural bases of higher cognitive functions* (pp. 543–571). New York: New York Academy of Sciences and MIT/Bradford Books.

Schacter, D. (1992). Priming and multiple memory systems: Perceptual mechanisms of implicit memory. *Journal of Cognitive Neuroscience, 4,* 244–256.

Schacter, D., Cooper, L., & Delaney, S. (1990). Implicit memory for possible and impossible objects: Constraints on the construction of structural descriptions. *Journal of Experimental Psychology: General, 17,* 3–19.

Schacter, D., Harbluk, J., & McLachlan, D. (1984). Retrieval without recollection: An experimental analysis of source amnesia. *Journal of Verbal Learning and Verbal Behavior, 23,* 593–611.

Seidenberg, M., & McClelland, J. (1989). A distributed, developmental model of word recognition and naming. *Psychological Review, 96,* 523–586.

Sejnowski, T. J., & Rosenberg, C. R. (1987). Parallel networks that learn to produce English text. *Complex Systems, 1,* 145–168.

Shimamura, A. (1985). Problems with the finding of stochastic independence as evidence for multiple memory systems. *Bulletin of the Psychonomic Society, 23,* 506–508.

Shimamura, A., & Squire, L. (1984). Paired-associate learning and priming effects in amnesia: A neuropsychological approach. *Journal of Experimental Psychology: General, 113,* 556–570.

Squire, L. (1992). Memory and hippocampus: A synthesis from findings with rats, monkeys, and humans. *Psychological Review, 99,* 195–231.

Squire, L., & Knowlton, B. (1995). Learning about categories in the absence of memory. *Proceedings of the National Academy of Sciences, USA, 92,* 12470–12474.

Squire, L., & Zola-Morgan, S. (1988). Memory: Brain systems and behavior. *Trends in Neurosciences, 11,* 170–175.

Stark, C. E. L. (1997). Repetition priming of words, pseudowords, and nonwords (Doctoral dissertation, Carnegie Mellon University, 1997). *UMI Dissertation Abstracts,* 59(02), p. 894 (University Microfilms No. AAT9823308).

Stark, C. E. L., & Squire, L. (in press). Recognition memory and familiarity judgments in severe amnesia: No evidence for a contribution of repetition priming. *Behavioral Neuroscience.*

Tenpenny, P. L. (1995). Abstractionist versus episodic theories of repetition priming and word identification. *Psychonomic Bulletin and Review, 2,* 339–363.

Tulving, E. (1985). How many memory systems are there? *American Psychologist, 40,* 385–398.

Tulving, E. (1987). Multiple memory systems and consciousness. *Human Neurobiology, 6,* 67–80.

Tulving, E., Schacter, D., & Stark, H. (1982). Priming effects in word-fragment completion are independent of recognition memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 8,* 336–341.

Von der Malsburg, C. (1973). Self-organizing of orientation sensitive cells in the striate cortex. *Kybernetik, 14,* 85–100.

Weiskrantz, L. (1990). Problems of learning and memory: One or multiple memory systems? *Philosophical Transactions of the Royal Society of London, Series B: Biological Sciences, 329,* 99–108.

Whitlow, J., & Cebollero, A. (1989). The nature of word frequency effects in perceptual identification. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 15,* 643–656.

Whittlesea, B. W. A., & Williams, L. D. (2000). The source of feelings of familiarity: The discrepancy-attribution hypothesis. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 26,* 547–565.

Wickelgren, W. (1979). Chunking and consolidation: A theoretical synthesis of semantic networks, configuring in conditioning, s-r versus cognitive learning, normal forgetting, the amnesic syndrome, and the hippocampal arousal system. *Psychological Review, 86,* 44–60.

Wilson, B., Baddeley, A., & Evans, J. (1994). Errorless learning in the rehabilitation of memory impaired people. *Neuropsychological Rehabilitation, 3,* 307–326.

Wilson, B., & Evans, J. (1996). Error-free learning in the rehabilitation of people with memory impairments. *Journal of Head Trauma Rehabilitation, 11,* 54–64.

Appendix

Stimuli From Experiments 1–5

Words	Pseudowords	Nonwords
	Experiment 1	
bond	corm	bdxj
bore	dask	bfdg
born	deto	bfxv
care	dild	bzvq
dear	dold	bzxp
deep	fude	dfjv
diet	hart	dkqj
draw	hipe	dpgv
ease	huly	fgdz
easy	jalk	fqpg
edge	jare	gbvj
evil	jolk	gbxd
fate	jopy	gdpz
fury	jort	gjzd
gain	kipe	jfgp
gaze	kise	jkpx
gulf	kize	jkxq
harm	moke	jqfg
hate	mopy	jvfz
lack	nopy	jxfb
leap	nund	jxkd
lift	pake	kbqd
list	palk	kpgv
mama	pran	kqbp
oily	puzz	kxfj
peak	rire	kzvb
poem	rumb	pfqg
reef	sask	vgjx
rely	sere	vjdz
ripe	sero	vjfx
sell	talm	vqgx
soft	tich	vxzk
soon	tike	vxzp
stay	tolk	xfgb
tiny	topy	xjdf
tour	vack	xvdz
trim	vash	xvfk
tyth	vess	xvjd
view	wint	zdjg
vote	zint	zxfb
	Experiment 2	
	bame	btfx
	barm	btmx
	bave	chtk
	bebt	cxhk
	belf	dxdj
	buly	dxdq
	bund	dxfq
	calt	dxpj
	cort	dxpk
	cude	dxsq
	cumb	jrfl
	dary	jrpl
	deap	ldnq
	deat	ldrk
	dend	ldsk
	dero	lfrx
	dord	lgbj
	dore	lghj
	dult	lgnj
	Experiment 2 (*continued*)	
	dure	lgpj
	dush	lgrj
	falm	lmdw
	febt	lmlw
	fept	ltbw
	fice	ltfq
	fich	lthj
	fild	ltlq
	fint	ltlw
	fity	ltnj
	fose	ltpw
	fove	ltrj
	fure	ltrw
	futy	mbcj
	hebt	mbhj
	helf	mblj
	hend	mbpj
	heny	mxbw
	hice	mxhw
	hish	mxpw
	hize	mxrw
	hort	ncfk
	houl	nchk
	huly	ncrk
	lare	nctk
	lebt	ndbj
	lold	ndcj
	lopy	ndhx
	lumb	ndrj
	meap	nghx
	melf	ngsx
	mept	ngvx
	mone	ntfx
	morm	ntsk
	mose	nxfq
	neaf	pghq
	nolt	pgmq
	nord	pgnq
	nush	pgsq
	pame	ptfx
	parm	ptlx
	pash	ptrx
	pich	pxsk
	pild	pxtk
	pinc	qtst
	plur	rdnq
	prad	rdtq
	pran	rgtw
	prap	rmhq
	pude	rmrq
	puty	rmsw
	rair	rmtq
	ralm	rqdx
	ralt	rqmx
	rarm	rqrx
	reaf	rtcq
	rean	rtdq
	rild	rthq
	rire	rtlq
	rist	rtlw
	rity	rtrq
	rold	rtsw

(*Appendix continues*)

Appendix (*continued*)

Words	Pseudowords	Nonwords
	Experiment 2 (*continued*)	
	rolt	rxdx
	rone	rxfj
	rore	rxhj
	rorm	rxlw
	rort	rxnj
	rure	rxzk
	salm	shdj
	sare	shnj
	sast	shpw
	seto	shrk
	sice	shsk
	sise	stbw
	sish	stzk
	sist	sxfk
	sorm	sxmq
	sove	sxpk
	spad	sxsq
	spus	sxtk
	stot	sxtq
	tast	tgcj
	tich	tgdk
	tise	tgfj
	tize	tghj
	topy	tgpj
	tord	tgrj
	trab	tqhx
	tran	tqlx
	valt	tqsx
	vame	txvw
	vart	vxlw
	vate	vxtq
	vave	wbsp
	velf	wbtr
	veny	wdsp
	vere	wfrx
	vero	wnhx
	zint	wpmx
	zire	wtlx
	zize	xnmx
	Experiment 3	
bare	bave	bdtx
bond	bopy	cdxk
calm	calt	crhk
colt	cond	crxw
copy	cort	fltk
curt	cune	jpsl
damp	darm	jsth
deaf	deat	lcmw
debt	dend	lctq
deny	deto	lfxk
dice	dift	lhgq
dish	dile	lhtw
drop	drou	lmdk
dumb	dush	lrgx
file	fice	lsfx
firm	fint	mdbj
fury	fure	mdpw
halt	hace	nbdq
hans	halm	ndgx
harm	hamp	nhsw

Words	Pseudowords	Nonwords
	Experiment 3 (*continued*)	
hate	hast	nldx
hire	hich	nptk
holy	horm	ntgk
lend	lebt	ntxj
lift	liny	nzxq
live	lish	pcgq
lord	lote	pstx
mild	mize	qdpr
neat	neaf	qtjh
norm	noly	rbxw
pint	pirm	rctj
pity	pise	rfgj
plus	plut	rfmk
pose	pone	rhmw
pray	prap	rhxk
pure	pumb	rldq
push	pury	rnmq
race	rans	rpxj
rely	rept	rstq
rest	rero	rtmx
rich	rire	rzqx
rise	rity	sdhk
save	sare	sphj
self	serm	spxq
sept	sest	srtx
shut	shus	srxk
size	sild	svtw
snap	snay	thxw
sort	solt	tpgk
span	spap	tvqx
term	telf	tvxq
thou	thop	vlxk
tiny	tive	vsxw
trap	tran	wdfx
tune	turt	wntx
vast	vate	wpgr
veto	veny	wsnp
vote	vord	wspn
zero	zely	wtpr
zone	zose	zsxk
	Experiment 4	
acid	bdzx	
atom	cdxk	
auto	cpxw	
base	dmxq	
beat	dnxj	
bold	fvxw	
busy	fvzq	
calm	jcxl	
clue	jpvl	
cope	jvlq	
cult	jvzh	
damp	jzrq	
dash	kjzn	
deaf	kmdw	
debt	kvml	
dice	kvzp	
diet	kwdc	
dumb	kxcp	

Appendix (*continued*)

Words	Pseudowords	Nonwords	Words	Pseudowords	Nonwords
Experiment 4 (*continued*)			Experiment 5		
earl	kzmr		bank	bame	
easy	lbdq		base	bant	
epic	lcmw		bend	bebt	
fame	lczj		best	belp	
fast	lfxk		bird	bist	
file	lhgq		blow	blon	
firm	lhzw		blue	blut	
flat	lqgk		boat	boam	
ford	lrxj		body	bork	
fury	lzxw		bowl	bote	
halt	mdbj		buck	bult	
harm	mdpw		burn	busk	
hero	mfxw		cady	cang	
hire	npzk		calm	carm	
holy	nrzx		cape	cawk	
hurt	nzdx		cent	cext	
idea	nzgk		city	cice	
item	nzxj		club	clur	
late	pcxq		coal	coan	
list	pzxg		coin	coid	
maid	qpzl		cult	cuck	
mean	qvpz		curb	culy	
mode	qwmz		damp	dage	
myth	qzjh		dark	dalt	
nude	rfdq		dash	dath	
oily	rfgj		debt	dest	
oral	rfmk		diet	diew	
pace	rhmw		dome	donk	
pint	rhqx		drag	drad	
pity	rhxk		duke	dube	
plot	rhzj		dumb	dulf	
plus	rxlw		duty	dury	
poem	rzmx		felt	ferd	
pose	rzxq		firm	fick	
rent	vbgj		fish	fild	
rise	vbxw		flux	flug	
rule	vdhw		foam	foat	
rush	vfzw		fond	foud	
safe	vlzk		four	fown	
shut	vpxq		fury	fuke	
site	vrhj		gain	gair	
slim	vrxk		gaze	gaxi	
snap	vxgw		girl	ging	
soft	wbzx		give	gire	
soul	wdfx		glad	glag	
span	wfzl		gram	grap	
spit	wmnx		grey	gred	
stay	wqlr		gulf	guty	
stop	wvgz		hair	hady	
tale	wvnp		half	hain	
tend	wvpn		harm	hape	
term	xdzk		hawk	hask	
thou	xkmz		help	helt	
tiny	xkwd		herd	hend	
tore	xpmq		hide	hine	
tour	zlxw		hold	hohn	
trim	zmhg		hope	hory	
tune	zpgk		hung	hure	
type	zvxk		john	jold	
unit	zwqj		joke	jose	
			july	jude	

(*Appendix continues*)

Appendix (*continued*)

Words	Pseudowords	Nonwords
	Experiment 5 (*continued*)	
jump	jurb	
kind	kimp	
knit	knip	
lack	lalk	
lawn	lary	
leap	leat	
lens	lely	
limp	lide	
line	lind	
lion	liow	
loan	loal	
loud	lour	
mate	marn	
meat	meap	
milk	mird	
mist	mise	
monk	mome	
move	mony	
myth	mype	
name	nake	
navy	nank	
neck	nent	
next	nerm	
nice	nity	
norm	nole	
nude	nump	
pace	pand	
path	pash	
peak	pead	
play	plar	
plea	plem	
plug	plux	
pole	pody	
pony	pomb	
pork	porm	
post	pove	
pure	pung	
quit	quin	
rake	ralm	
rang	ravy	
read	reak	
rely	rens	
rich	rign	
ripe	riny	
rose	roke	

Words	Pseudowords	Nonwords
	Experiment 5 (*continued*)	
ruin	ruit	
rusk	rurn	
salt	sace	
sand	sark	
save	sast	
scar	scay	
self	seto	
shed	shey	
shut	shue	
sick	sipe	
sign	sirl	
sing	sish	
snap	snam	
sort	sone	
spot	spop	
spur	spub	
stem	stea	
stop	stot	
swim	swin	
task	talf	
taxi	taze	
term	teck	
thin	thim	
tiny	tich	
tire	tive	
tomb	tond	
tory	tope	
town	tost	
trip	trit	
tube	tumb	
type	tyth	
vary	vack	
vast	vave	
veto	velf	
view	viet	
void	voin	
vote	vowl	
wage	wamp	
walk	wase	
want	wawn	
wild	wilk	
wise	wirm	
yarn	yate	
zone	zort	

Received October 14, 1998
Revision received December 15, 1999
Accepted December 16, 1999 ■