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The frequency effect for pseudowords in the lexical decision task

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Four experiments were designed to investigate whether the frequency of words used to create pseudowords plays an important role in lexical decision. Computational models of the lexical decision task (e.g., the dual route cascaded model and the multiple read-out model) predict that latencies to low-frequency pseudowords should be faster than latencies to high-frequency pseudowords. Consistent with this prediction, results showed that when the pseudowords were created by replacing one internal letter of the base word (Experiments 1 and 3), high-frequency pseudowords yielded slower latencies than low-frequency pseudowords. However, this effect occurred only in the leading edge of the response time (RT) distributions. When the pseudowords were created by transposing two adjacent internal letters (Experiment 2), high-frequency pseudowords produced slower latencies in the leading edge and in the bulk of the RT distributions. These results suggest that transposed-letter pseudowords may be more similar to their base words than replacement-letter pseudowords. Finally, when participants performed a go/no-go lexical decision task with one-letter different pseudowords (Experiment 4), high-frequency pseudowords yielded substantially faster latencies than low-frequency pseudowords, which suggests that the lexical entries of high-frequency words can be verified earlier than the lexical entries of low-frequency words. The implications of these results for models of word recognition and lexical decision are discussed.

One fundamental issue for any computational model of visual word recognition and lexical decision is how "yes" and "no" decisions are made. Virtually all researchers assume that a "yes" decision occurs when a quality criterion is reached: A "yes" response is initiated when the activity of a whole-word representation in the lexical level reaches threshold or when the overall activity in the orthographic lexicon reaches threshold (dual route cascaded [DRC] model, Coltheart, Rastle, Perry, Langdon, & Ziegler, 2001; multiple read-out model [MROM], Grainger & Jacobs, 1996). But how do participants make "no" responses? The two most widely tested computational models for the lexical decision task (i.e., the DRC model and MROM) use a deadline criterion for "no" responses that is based on the proposal by Coltheart, Davelaar, Jonasson, and Besner (1977). Coltheart et al. (1977) suggested that participants make "no" responses via extra-stimulus information—namely, a flexible deadline criterion: If lexical activation (in terms of the sum of activation in the orthographic lexicon) is high early in processing, the deadline can be increased; if there is very little activation in the orthographic lexicon, the deadline can be shortened (Coltheart et al., 1977; Coltheart et al., 2001; Grainger & Jacobs, 1996). The deadline account correctly predicts that responses to pseudowords with many similarly spelled words are slower and more accurate than the correct responses to pseudowords with few similarly spelled words (Coltheart et al., 1977; see also Carreiras, Perea, & Grainger, 1997; Forster & Shen, 1996, among others).

One straightforward prediction of the deadline account is the presence of a pseudoword frequency effect. In activation-based models such as the DRC model or the MROM, high-frequency words have higher resting activation levels than low-frequency words. This implies that, other things being equal, pseudowords formed from a high-frequency word (henceforth referred to as "high-frequency pseudowords"; e.g., PEOGLE; the base word would be PEOPLE) generate *more* activity in the orthographic lexicon at the early stages of word processing than those pseudowords formed from a low-frequency word ("low-frequency pseudowords," DIURMAL; the base

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word would be DIURNAL). Thus, the deadline in the MROM or in the DRC model should be set longer for high-frequency pseudowords than for low-frequency pseudowords, and hence latencies to high-frequency pseudowords should be *slower* than the latencies to low-frequency pseudowords (see also Balota & Chumbley, 1984). It is important to note that, given that this deadline mechanism depends on the degree of activation at the early stages of word processing, the faster responding of low-frequency pseudowords (relative to high-frequency pseudowords) should be evident in the leading edge of the response time (RT) distributions (e.g., see Ratcliff, Gómez, & McKoon, 2004, for analyses of the mean RTs and the .1 quantiles in lexical decision).

Interestingly, the predictions for frequency-ordered search/verification models are quite different (activation-verification model, Paap, Newsome, McDonald, & Schvaneveldt, 1982; search model, Forster, 1976, 1989). In the framework of Paap et al.'s (1982) activation-verification model, after a stage that involves the initial analysis of sensory information that leads to the activation of lexical units in the mental lexicon (the "activation" stage), there is an independent top-down analysis of the stimulus that is sensitive to deviations from the stored representation of a word (i.e., the "verification" stage). The lexical candidates are verified in terms of frequency, which implies that the lexical units activated by a high-frequency pseudoword are checked before the lexical units activated by a low-frequency pseudoword. As a result, high-frequency pseudowords could be discarded earlier than the low-frequency pseudowords and, unlike the predictions of the DRC model and the MROM, a facilitative effect of pseudoword frequency would occur.[1] Finally, what should also be noted is that this "verification" stage is posited to occur at a relatively late stage in word processing, so that this facilitative pseudoword frequency effect should be evident in the tail—rather than in the leading edge—of the RT distributions.

The experimental evidence for a frequency effect with pseudowords created by replacing letters from the base word (RL pseudowords, for short) is not conclusive. Some reports revealed more accurate and/or faster responding for RL high-frequency pseudowords than for RL low-frequency pseudowords (e.g., Allen & Emerson, 1991; den Heyer, Goring, Gorgichuk, Richards, & Landry, 1988; Duchek & Neely, 1989; Stanners, Jastrzembski, & Westbrook, 1975), other reports yielded a null effect (e.g., Allen, McNeal, & Kvak, 1992; Frederiksen & Kroll, 1976; Grainger & Jacobs, 1996; Paap & Johansen, 1994), and several reports showed faster responding for RL low-frequency pseudowords (Arduino & Burani, 2004; Rajaram & Neely, 1992). What should also be noted is that only two of the studies cited above with a significant pseudoword frequency effect reported an analysis by items (Arduino & Burani, 2004; Stanners et al., 1975). (To generalize the results not only to a subject population but also to an item population, it is essential to conduct the analysis by items; see Clark, 1973; Raaijmakers, Schrijnemakers, & Gremmen, 1999.) Furthermore, the way in which the RL pseudowords were created was not the same in all the experiments,[2] and the number of letters in the stimuli was highly variable across the studies (from three up to nine letters). Obviously, the best option for studying the effect of pseudoword frequency is to employ relatively long items, so the pseudowords will retain the orthographic/phonological structure of the words from which they were derived (see Frederiksen & Kroll, 1976); then it will be obvious, at least in most cases, what particular word they are derived from (see Forster & Veres, 1998, for a discussion of this issue).

Unlike the mixed results with RL pseudowords, findings from the two published reports that manipulated the frequency of transposed-letter (TL) pseudowords (e.g., MOHTER) produced the same pattern of effects: more errors and longer latencies for the high-frequency pseudowords (Andrews, 1996; O'Connor & Forster, 1981). Specifically, O'Connor and Forster found that TL high-frequency pseudowords (e.g., MOHTER) were responded to less accurately than TL low-frequency pseudowords (e.g., BOHTER, error rates: 24.1% vs. 11.0%, respectively). The latency analysis showed the same pattern (i.e., slower RTs for the TL high-frequency pseudowords than for the TL low-frequency pseudowords; 678 vs. 634 msec), but the effect was not significant. More recently, Andrews (1996) also found slower and less accurate responding for TL high-frequency pseudowords than for TL low-frequency pseudowords (736 vs. 706 msec; error rates: 10.9% vs. 5.7%, respectively), although the only significant effect occurred in the analysis of error data by subjects.

One reason why the pseudoword frequency effect may be more consistent for TL pseudowords than for RL pseudowords is that TL pseudowords are more perceptually similar to their base words than RL pseudowords (Chambers, 1979; see also Andrews, 1996; Davis, 1999; Perea & Lupker, 2003a, 2003b), and thus the pseudoword frequency effect should be more powerful for TL pseudowords than for RL pseudowords. Indeed, TL pseudowords (e.g., JUGDE) can be easily misidentified as words (see Bruner & O'Dowd, 1958; O'Connor & Forster, 1981). Keep in mind that, although RL pseudowords share more characters in the same position from the original word, TL pseudowords keep *all* orthographic characters from the original word. Consistent with this view, Perea and Lupker (2003a) found a more robust masked associative priming effect in the lexical decision task when the prime was a TL pseudoword (*jugde*–COURT) than when the prime was a RL pseudoword (*judpe*–COURT). Likewise, it has been claimed that the word TRAIL may be inhibited to a larger degree by its TL-neighbor TRIAL than by its RL-neighbor TRAIN (see Andrews, 1996). (For simplicity's sake, we defer a discussion of the choice of a coding scheme in models of visual word recognition until the General Discussion.)

In sum, the main goal of the present study was to investigate whether the frequency of the words used to create pseudowords plays an important role in lexical decision. In Experiment 1, high- and low-frequency pseudowords were created by replacing one interior letter of a high- or a low-frequency word (RL pseudowords), whereas in Experiment 2 high- and low-frequency pseudowords were created by transposing two internal letters of a high- or low-frequency word (TL pseudowords). (For comparison purposes with the RL high-frequency pseudowords, we also included TL high-frequency pseudowords in Experiment 1.) We chose to replace/transpose internal letters since the effects of orthographic similarity are stronger when the transposition/replacement occurs in middle letters (e.g., Chambers, 1979; Perea, 1998; Perea & Lupker, 2003a, 2003b). Word and pseudoword stimuli in Experiment 1 were presented to different groups of participants under different exposure durations: Items were presented for unlimited time, items were presented for 150 msec and were immediately masked, and items were presented for 150 msec and were immediately erased instead of being masked. (The word stimuli were high-, low-, and very low frequency words.) The rationale for including a condition with brief/masked items was to maximize the chances of a pseudoword frequency effect (i.e., more errors to high-frequency pseudowords; see Forster, 1989; Paap, Johansen, Chun, & Vonnahme, 2000): The brief/masked presentations will presumably lead to the application of a relatively lenient decision criterion that allows "word" responses to be made without a perfect match between sensory and lexical representations. To unconfound exposure duration and masking, the stimuli were also presented briefly (150 msec) but without a mask. A brief duration maximizes opportunity for misperceptions relative to an unlimited viewing condition, but not to the same degree as a masked presentation. Not surprisingly, the DRC model and the MROM predict a longer deadline for high-frequency pseudowords than for low-frequency pseudowords with our stimuli: The summed lexical activation values after seven processing cycles with the interactive-activation model (the core model for both the DRC model and the MROM) for the high- and low-frequency pseudowords are 0.32 and 0.26, respectively, and hence the deadline for "no" responses is posited to be longer for the high-frequency pseudowords than for the low-frequency pseudowords.

Experiment 2 was a replication of Experiment 1 (with unlimited viewing time), except that the high- and low-pseudowords were created by transposing two internal letters. In Experiment 2, we also included a set of distant pseudowords, which were created by substituting two internal letters from a base word. In this light, evidence that the word whose letters were transposed was activated would be provided by slower and/or less accurate classification of TL low-frequency pseudowords compared with the distant pseudowords. Experiment 3 manipulates pseudoword frequency with RL pseudowords (with unlimited viewing time), this time with longer items (eight-letter items instead of the six-letter items used in Experiments 1–2). As in Experiment 2, we also included a control condition with distant pseudowords. Experiment 4 was a go/no-go replication of Experiment 3.

In the present experiments we examined not only the mean RTs per condition, but also the RT distributions, especially the leading edge (or onset) of the RT distributions. Bear in mind that RT distributions have a long story in psychology (see Woodworth, 1938) and they provide more valuable information than the mere analysis of the mean RTs (e.g., Andrews & Heathcote, 2001; Balota & Spieler, 1999; Perea, Rosa, & Gómez, 2002, 2003; Ratcliff, 1978, 1979; Ratcliff & Murdock, 1976; Ratcliff, Perea, Colangelo, & Buchanan, 2004; see also Ratcliff, Gómez, & McKoon, 2004, for an extensive discussion of the advantages of using RT distributions in the lexical decision task). The reason for examining the leading edge of the RT distributions is that fast responses may be influenced mostly by an early activation process (e.g., a deadline mechanism on the basis of early lexical activation, as in the MROM and the DRC model) rather than by a late verification process (as in an activation-verification model). For instance, the lack of a consistent pseudoword frequency effect on the mean RT (for RL pseudowords) in prior research may be due to the fact that, for "no" responses, there are two opposite processes at play: a deadline mechanism on the basis of early activation that favors fast responses to low-frequency pseudowords, and a late verification mechanism that may benefit high-frequency pseudowords.

EXPERIMENT 1

Method

Participants. Seventy-two psychology students from the University of Valencia took part in the experiment for course credit. All of them had either normal or corrected-to-normal vision and were native speakers of Spanish.

Materials. One hundred and twenty Spanish words of six letters in length were collected on the basis of the word frequency norms for Spanish (Alameda & Cuetos, 1995). Forty of these words were of high frequency, 40 of low frequency, and 40 of very low frequency. Frequency counts for high-frequency words were greater than 63 per million (mean = 174, range = 70–499), frequency counts for the low-frequency words were greater than 7 and less than 13 (mean = 10, range = 8–12), and frequency counts for the very low frequency words were less than 3 (mean = 1.2, range = 1–2).

The target pseudowords consisted of 40 stimuli constructed by changing an interior letter from a low-frequency six-letter Spanish word (e.g., GOPERA; the word would be GOTERA, the Spanish for *leak*; mean number of word neighbors [or Coltheart's N] = 1.7, range = 1–7; note that no Spanish words of a frequency of occurrence higher than four per million could be formed by changing a letter from these pseudowords), 80 stimuli constructed by changing an interior letter (consonant or vowel) from a high-frequency six-letter Spanish word (e.g., LÓGECA; the word would be LÓGICA, the Spanish for *logic*; mean Coltheart's N = 1.7, range = 1–6), and 80 stimuli constructed by transposing two adjacent interior letters from these same high-frequency words (e.g., LÓIGCA; the word would be LÓGICA; mean number of word neighbors = 0.1, range = 0–2; note that no high-frequency words could be formed by changing a letter from these pseudowords). The mean positional bigram frequencies were 148, 162, and 132 for the RL low-frequency pseudowords, RL high-frequency pseudowords, and TL pseudowords, respectively, and they were calculated using a token count, as recorded in Álvarez, Carreiras, and de Vega (1992). The difference in positional bigram frequency between RL high- and low-frequency pseudowords was far from statistical significance [$F(1,119) = 1.46, p > .20$].

In order to avoid the potential problem that the same base words might be used for creating the RL high-frequency pseudowords and the TL high-frequency pseudowords (e.g., LÓGECA and LÓIGCA), we created two lists of items. No list contained both the RL high-frequency pseudoword (e.g., LÓGECA) and its corresponding TL pseudoword (LÓIGCA). Each list contained equal numbers of high-frequency words (40), low-frequency words (40), very low frequency words (40), RL low frequency pseudowords (40), RL high frequency pseudowords (40), and TL pseudowords (40). Twelve participants were run on each list and experiment.

Design. For pseudowords, viewing time (unlimited viewing time, brief/masked, brief/unmasked) was varied between subjects (24 participants were assigned to each level of this factor), whereas pseudoword frequency (RL low-frequency pseudoword, RL high-frequency pseudoword) varied within subjects. For words, word frequency (high frequency, low frequency, very low frequency) varied within subjects. Each participant was given a total of 240 experimental trials: 120 word trials and 120 pseudoword trials. (We will focus on the comparison between RL high- and low-frequency pseudowords rather than on the comparison between TL high-frequency pseudowords and RL high-frequency pseudowords given that TL pseudowords had an illegal bigram on a number of cases and tended to have fewer word "neighbors.")

Procedure. Participants were tested in groups of 4 to 8 in a quiet room. Presentation of the stimuli and recording of RTs were controlled by Apple Macintosh Classic II computers. The routines for controlling stimulus presentation and collecting RTs were obtained from Lane and Ashby (1987) and from Westall, Perkey, and Chute (1986), respectively. Stimuli were presented on the monitor in 12-point Courier font. On each trial, a fixation signal (> <) was presented for 200 msec on the center of the screen. After a 50-msec blank screen, a lowercase letter string was presented at the center of the screen. In the unlimited viewing time condition, the stimulus item remained on the screen until the participant made a response. In the brief/masked condition, the stimulus item was presented for 150 msec and was immediately replaced by a masking pattern consisting of a string of six number signs (#). In the brief/unmasked condition, the stimulus item was presented for 150 msec and was immediately erased. Participants were instructed to press one of two buttons on the keyboard to indicate whether the letter string was a Spanish word or not. Participants used their dominant hand to make the word response. Participants were requested to respond as rapidly and as accurately as possible. RTs were measured from the onset of the letter string until the participant's response. The intertrial interval was 400 msec. Each participant received a different random order of stimuli. Each participant received a total of 24 practice trials prior to the experimental phase. The session lasted approximately 15 min.

Results and Discussion

Lexical decision latencies less of than 250 msec or greater than 1,500 msec (less than 0.7% for pseudowords and less than 1.5% for words) were excluded from the mean RT analyses.[3] To examine RT distributions, we used *all* the correct RTs of each participant to estimate five quantile RTs: the .1, .3, .5, .7, and .9 quantiles (see Ratcliff, Gómez, & McKoon, 2004; Ratcliff, Perea, et al., 2004, for a similar procedure). Figure 1 shows the five quantiles for responses to the stimuli. The starting point (or leading edge) of the RT distributions is represented by the .1 quantile (i.e., the circle at the bottom of each col-

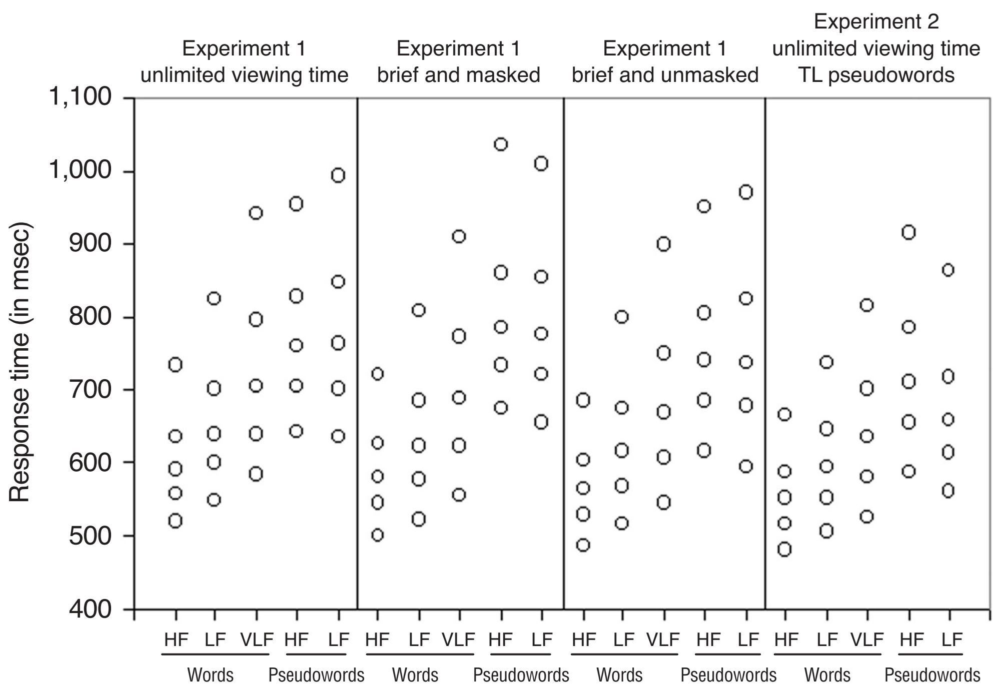

Figure 1. Group RT distributions for correct responses to word and pseudoword stimuli in Experiments 1 and 2. The circles represent the .1, .3, .5, .7, and .9 quantiles for a given stimulus type: the first circle from bottom to top represents the .1 quantile, the second circle the .3 quantile, and so on. Note—HF, LF, and VLF: high-frequency words, low-frequency words, and very low frequency words, respectively.

Table 1
Mean Lexical Decision Response Times (in Milliseconds), Response Times at the .1 Quantile (Q), and Percent Errors (PE) for the Pseudoword Targets in Experiment 1

	Pseudoword Category									Difference Score (HF − LF)		
	RL LF			RL HF			TL HF					
	M	Q	PE	*M*	Q	PE	*M*	Q	PE	*M*	Q	PE
Unlimited viewing time	789	635	6.9	780	644	4.7	767	632	4.6	−9	9	−2.2
Brief/masked	801	657	10.5	812	674	18.5	815	663	38.0	11	14	8.0
Brief/unmasked	759	594	10.3	760	617	10.6	725	604	15.4	1	23	0.3

Note—The Difference Score column refers to the difference between the RL HF pseudowords and the RL LF pseudowords. HF, LF: high- and low-frequency words, respectively.

umn), and the skews are represented by the spread of the higher quantiles.

We conducted analyses of variance (ANOVAs) on the correct mean RTs, .1 quantiles, and percentage of errors for subjects (F_1) and for items (F_2). For the pseudoword data, statistical analyses were conducted to assess the effect of pseudoword frequency (RL low-frequency pseudowords vs. RL high-frequency pseudowords) and the effect of viewing time (unlimited viewing time, brief/masked, brief/unmasked). In addition, for the word data, ANOVAs were conducted to analyze the effect of word frequency (high, low, very low) and the effect of viewing time (unlimited viewing time, brief/masked, brief/unmasked). Reported effects were significant at the $p < .05$ level unless otherwise noted. The mean RT, the .1 quantile, and the percent error from the subject analysis are presented in Tables 1 and 2.

Pseudoword data. The ANOVAs on the leading edge of the RT distributions (.1 quantile) showed that, on average, RL low-frequency pseudowords had faster latencies than RL high-frequency pseudowords in the analysis by subjects [$F_1(1,66) = 17.49$, $MS_e = 562.8$; $F_2(1,117) = 0.42$, $MS_e = 9{,}657.6$]. Neither the main effect of viewing time nor the interaction between viewing time and pseudoword frequency approached significance (all ps $> .15$). The ANOVAs on correct mean RTs failed to show any significant effects (the difference between high- and low-frequency pseudowords was less than 1 msec).

The ANOVAs on the error data showed that, on average, participants made more errors to RL high-frequency pseudowords than to RL low-frequency pseudowords, and this effect was significant in the analysis by subjects [$F_1(1,69) = 6.26$, $MS_e = 21.15$; $F_2(1,118) = 2.71$, $MS_e = 123.78$, $p > .10$]. The main effect of viewing time was also significant [$F_1(2,69) = 7.6$, $MS_e = 121.14$; $F_2(2,236) = 8.31$, $MS_e = 36.04$]. More importantly, the viewing time × pseudoword-frequency interaction was significant [$F_1(2,69) = 14.07$, $MS_e = 24.15$; $F_2(2,236) = 36.04$, $MS_e = 90.94$]. This interaction suggests that when the items were presented briefly and masked, participants made more errors to high- than to low-frequency pseudowords [$F_1(1,23) = 22.03$, $MS_e = 35.05$; $F_2(1,118) = 97.56$, $MS_e = 78.71$]. When the items were presented briefly and unmasked, there was no sign of an effect of pseudoword frequency (both ps $> .20$), whereas when the items were presented under unlimited viewing time, there were more errors to low- than to high-frequency pseudowords in the analysis by subjects [$F_1(1,23) = 4.47$, $MS_e = 12.86$; $F_2(1,118) = 3.38$, $MS_e = 78.71$, $p = .07$].

Word data. The ANOVAs on the mean RTs showed a significant effect of word frequency (i.e., faster responding to higher frequency words than to lower frequency

Table 2
Mean Lexical Decision Response Times (in Milliseconds), Response Times at the .1 Quantile (Q), and Percent Errors (PE) for the Word Targets in Experiments 1–4

	Word Frequency												Difference Score (VLF − LF)		
	HF			LF			VLF			VLF − HF					
	M	Q	PE	*M*	Q	PE	*M*	Q	PE	*M*	Q	PE	*M*	Q	PE
	Experiment 1														
Unlimited viewing time	611	519	1.7	669	550	3.6	734	583	10.0	123	64	8.3	65	33	6.4
Brief and masked	599	499	1.9	648	525	5.4	709	555	12.2	110	56	10.3	61	30	6.8
Brief and unmasked	580	487	2.4	639	516	5.0	694	544	15.9	114	57	13.5	55	28	10.9
	Experiment 2														
Unlimited viewing time	567	479	0.9	612	505	3.5	657	526	9.0	90	47	8.1	45	21	5.5
	Experiment 3														
Unlimited viewing time	661	543	1.6	755	584	8.9				94	41	7.3			
	Experiment 4														
Unlimited viewing time	–	–	1.3	–	–	4.8				–	–	3.5			

Note—HF, LF, and VLF: high-frequency words, low-frequency words, and very low frequency words, respectively.

words) [$F_1(2,138) = 313.6$, $MS_e = 770.7$; $F_2(2,117) = 84.77$, $MS_e = 5{,}213.6$]. The main effect of viewing time was not significant in the analysis by subjects [$F_1(2,69) = 1.15$, $MS_e = 17{,}604.6$; $F_2(2,234) = 42.66$, $MS_e = 722.3$]. There were no signs of an interaction between the two factors (both Fs < 1). Again, the word frequency effect did not simply reflect a shift of the RT distributions; it was also accompanied by a change in the shape of the distributions (see also Balota & Spieler, 1999; Ratcliff, Gómez, & McKoon, 2004): The lower the frequency, the more skewed were the RT distributions (Figure 1).

The ANOVAs on the error data showed a significant effect of word frequency (i.e., more errors to lower frequency words than to higher frequency words) [$F_1(2,138) = 126.55$, $MS_e = 17.74$; $F_2(2,117) = 24.58$, $MS_e = 151.96$]. The effect of viewing time and the interaction between the two factors were also significant [$F_1(2,69) = 3.55$, $MS_e = 36.29$; $F_2(2,234) = 8.35$, $MS_e = 25.71$; and $F_1(4,138) = 3.15$, $MS_e = 17.74$; $F_2(4,234) = 3.62$, $MS_e = 25.71$, respectively].

The present experiment revealed faster RTs corresponding to "no" responses to low- than to high-frequency pseudowords, as predicted by the DRC model and the MROM. However, this effect occurred only in the leading edge of the RT distributions (a 17-msec effect in the .1 quantile), and it disappeared in the bulk of the RT distributions (the size of the effect was 1 msec in the mean RTs, and the effect was also negligible in the median RTs: 758 msec for RL high- vs. 762 msec for RL low-frequency pseudowords). We also found more errors to high- than to low-frequency pseudowords, although this effect was restricted to the case in which the items were presented briefly (150 msec) and masked.

Although the focus of Experiment 1 was on the pseudoword frequency effect for RL pseudowords (high- vs. low-frequency pseudowords), we included a third condition with TL high-frequency pseudowords. It may be worth noting that these TL high-frequency pseudowords were highly competitive under masking conditions (error rates: 38%); the corresponding error rate for the RL high-frequency pseudowords was substantially lower (18%) [$F_1(1,23) = 32.79$, $MS_e = 138.85$; $F_2(1,78) = 58.54$, $MS_e = 259.70$]. This finding reinforces the view that TL pseudowords are highly similar to their base words (see Davis, 1999; Perea & Lupker, 2003a, 2003b, 2004). (This effect did not occur under unlimited viewing time, possibly because some of the TL pseudowords had an illegal or infrequent bigram [e.g., *LÓIGCA*] and also tended to have fewer orthographic neighbors than the orthographically legal RL pseudowords.)

Experiment 2 examined the existence of a frequency effect with TL pseudowords (TL high- vs. TL low-frequency words) under unlimited viewing time. In this experiment, we also included a set of distant pseudowords, which were created by substituting two internal letters from a base word. Evidence that the word whose letters were transposed was activated would be provided by slower and/or less accurate classification of TL pseudowords compared with control pseudowords. The three conditions (TL high frequency, TL low frequency, and control pseudowords) were matched on the legality of the syllabic structure.

EXPERIMENT 2

Method

Participants. Twenty-four psychology students from the University of Valencia took part in the experiment for course credit. All of them had either normal or corrected-to-normal vision and were native speakers of Spanish. None of them had taken part in the previous experiment.

Materials. The target pseudowords were 40 stimuli constructed by transposing two interior letters from a low-frequency six-letter Spanish word (e.g., *GOETRA*; the word would be *GOTERA*; mean Coltheart's $N = 0.1$, range = 0–2; note that no Spanish words of a frequency of occurrence higher than four per million could be formed by changing a letter from these pseudowords), 80 TL high-frequency pseudowords (e.g., *LÓIGCA*; the word would be *LÓGICA*; mean number of word neighbors = 0.1, range = 0–2), and 80 stimuli constructed by changing two interior letters from these same high-frequency words (pseudoword control, e.g., *LÓUTCA*; the word would be *LÓGICA*; mean number of word neighbors = 0.1, range = 0–1; note that no Spanish words of a frequency of occurrence higher than six per million could be formed by changing a letter—or transposing two adjacent letters—from these pseudowords). The percentage of pseudowords that were not easily pronounceable and the percentage of pseudowords with an infrequent spelling in Spanish (e.g., an illegal syllable) were the same in each condition (15% and 55%, respectively). We used the same target words as in Experiment 1.

As in Experiment 1, two lists of the items were formed so that each list contained equal numbers of high-frequency words (40), low-frequency words (40), very low frequency words (40), TL low-frequency pseudowords (40), TL high-frequency pseudowords (40), and TL high-frequency pseudoword controls (40). No list contained both the TL high-frequency pseudoword (e.g., *LÓIGCA*) and the TL pseudoword control (*LÓUTCA*). Twelve participants were run on each list.

Design and Procedure. For pseudowords, pseudoword frequency (TL high- vs. TL low-frequency pseudoword) was varied within subjects. For words, word frequency (high frequency, low frequency, very low frequency) was varied within subjects. Each participant was given a total of 240 experimental trials: 120 word trials and 120 pseudoword trials. The procedure was the same as in Experiment 1 under unlimited viewing time.

Results and Discussion

Lexical decision times of less than 250 msec or greater than 1,500 msec were excluded from the mean RT analyses (less than 0.14% for pseudowords and words). The RT distributions for the different conditions are presented in Figure 1. The mean RT, the .1 quantile, and percent error for pseudoword and word targets from the subject analysis are presented in Tables 3 and 2, respectively.

Pseudoword data. The ANOVA on the .1 quantile showed that latencies to TL low-frequency pseudowords were 26 msec shorter than the latencies to TL high-frequency pseudowords (561 vs. 587 msec, respectively) [$F_1(1,23) = 8.70$, $MS_e = 886.2$; $F_2(1,118) = 16.23$, $MS_e = 3{,}459.6$]. The ANOVA on the mean RTs also showed that latencies to TL low-frequency pseudowords were 44 msec shorter than the latencies to TL high-frequency pseudowords (671 vs. 734 msec, respectively) [$F_1(1,23) = 67.76$, $MS_e = 352.7$; $F_2(1,118) = 12.70$, $MS_e = 4{,}620.2$]. Finally, the ANOVA on the error data

Table 3
Mean Lexical Decision Response Times (in Milliseconds), Response Times at the .1 Quantile (Q), and Percent Errors (PE) for the Pseudoword Targets in Experiment 2

Pseudoword Category									Difference Score (HF − LF)		
TL LF			TL HF			TL Control					
M	Q	PE	*M*	Q	PE	*M*	Q	PE	*M*	Q	PE
690	561	4.9	734	587	12.8	671	553	2.5	44	26	7.9

Note—HF, LF: high- and low-frequency words, respectively.

showed that participants made fewer errors on TL low-frequency pseudowords than on TL high-frequency pseudowords (4.9% vs. 12.8% of errors, respectively) [$F_1(1,23) = 22.75$, $MS_e = 33.1$; $F_2(1,119) = 12.46$, $MS_e = 134.1$].

Word data. The ANOVA on the mean RT showed a significant effect of word frequency [$F_1(2,46) = 165.59$ $MS_e = 295.2$; $F_2(2,117) = 56.60$, $MS_e = 1{,}601.3$]. The ANOVA on the error data also showed a robust effect of word frequency [$F_1(2,46) = 30.57$, $MS_e = 13.15$; $F_2(2,117) = 11.54$, $MS_e = 58.05$].

The results of the present experiment are clear-cut. First, we found faster latencies for low- than for high-frequency pseudowords, replicating Andrews (1996) and O'Connor and Forster (1981) with a more powerful design: Unlike the findings from those experiments, the effect here was significant in the analysis by subjects and items on both the error data and the latency data. Second, the less competitive role played by the TL low-frequency pseudowords (relative to the TL high-frequency pseudowords) was *not* due to the fact that these items did not activate their corresponding base words: TL low-frequency pseudowords produced slower latencies and more errors than the distant, control pseudowords [mean RT analysis, 690 vs. 671 msec, respectively; $F_1(1,23) = 6.89$, $MS_e = 580.1$; $F_2(1,118) = 3.31$, $MS_e = 2959.6$, $p = .071$; error analysis, 4.9 vs. 2.5% of errors, respectively; $F_1(1,23) = 4.57$, $MS_e = 15.08$; $F_2(1,118) = 4.76$, $MS_e = 32.22$].

EXPERIMENT 3

Experiments 1 and 2 showed that the high-frequency pseudowords generated more lexical activation than the low-frequency pseudowords: A significant effect of pseudoword frequency was found both in the leading edge of the RT distribution (.1 quantile) and in the number of false positives. However, in the case of RL pseudowords, the pseudoword frequency effect at the .1 quantile was not significant in the analysis by items, and the pseudoword frequency effect in the error data appeared only when the items were presented briefly and masked. Thus, we thought that it was important to replicate this finding with a more powerful design.

To maximize the chances of obtaining a more robust pseudoword frequency effect with RL pseudowords, we decided to use longer (eight-letter) items in Experiment 3. The idea is that RL pseudowords of eight letters are more likely to activate (i.e., to a higher degree) their corresponding base words than the RL pseudowords of six letters. (Bear in mind that each RL pseudoword shares seven out of eight letters with its corresponding base word.) To increase experimental power, the number of items per condition was now 50 (it was 40 in Experiments 1–2). To verify that the RL low-frequency pseudowords were indeed activated, we employed control, distant pseudowords by replacing two internal letters from a legitimate word. Thus, evidence that the base word of the RL low-frequency pseudoword was activated would be provided by slower and/or less accurate classification of RL low-frequency pseudowords compared with the distant pseudowords.

Method

Participants. Twenty-two psychology students from the University of Valencia took part in the experiment for course credit. All of them had either normal or corrected-to-normal vision and were native speakers of Spanish. None of them had taken part in the previous experiments.

Materials. One hundred and fifty Spanish words of eight letters in length were collected on the basis of the word frequency norms for Spanish (Alameda & Cuetos, 1995). Seventy-five of these words were of high frequency and 75 of low frequency. Frequency counts for high-frequency words were greater than 40 per million words (mean = 68, range = 41–353), and frequency counts for the low-frequency words were less than 6 (mean = 4, range = 3–5).

The target pseudowords consisted of 50 stimuli constructed by randomly changing an interior letter from a low-frequency Spanish word of eight letters (e.g., RESITUAL; the word would be RESIDUAL; mean number of word neighbors = 1.2, range = 1–2; note that no Spanish words of a frequency of occurrence higher than four per million could be formed by changing a letter from these pseudowords), 50 stimuli constructed by randomly changing an interior letter from a high-frequency Spanish word of eight letters (e.g., VOLURTAD; the word would be VOLUNTAD; mean number of word neighbors = 1.2, range = 1–2), and 50 stimuli constructed by randomly replacing two interior letters from Spanish words of eight letters (e.g., ARALEMIA; the word would be ACADEMIA; mean number of word neighbors = 0.0, range = 0–0). The mean token positional bigram frequencies were 148, 150, and 148 for the RL low-frequency pseudowords, RL high-frequency pseudowords, and control pseudowords, respectively, in the bigram count of Álvarez et al. (1992). All the pseudowords were orthographically and phonologically legal in Spanish.

Design. For pseudowords, pseudoword frequency (RL low-frequency pseudoword, RL high-frequency pseudoword) varied within subjects. For words, word frequency (high frequency, low frequency) also varied within subjects. Each participant was given a total of 300 experimental trials: 150 word trials and 150 pseudoword trials.

Procedure. The procedure was the same as in Experiment 1 under unlimited viewing time.

Results and Discussion

Lexical decision latencies less than 250 msec or greater than 1,500 msec (less than 3.3% for pseudowords and less than 1.1% for words) were excluded from the mean RT analyses. For the pseudoword data, statistical analyses were conducted to analyze the effect of pseudoword frequency (RL low- vs. RL high-frequency pseudowords). For the word data, ANOVAs were conducted to analyze the effect of word frequency (high vs. low). The mean RT, the .1 quantile, and percent error from the subject analysis are presented in Tables 2 and 4. Figure 2 shows the five quantiles for responses to the stimuli.

Pseudoword data. The ANOVAs on the leading edge of the RT distributions (.1 quantile) showed that, on average, low-frequency pseudowords had faster latencies than high-frequency pseudowords (658 vs. 683 msec, respectively) [$F_1(1,21) = 10.13$, $MS_e = 650.2$; $F_2(1,98) = 21.79$, $MS_e = 3{,}289.8$].

The ANOVAs on the error data showed that, on average, participants made more errors to high- than to low-frequency pseudowords (15.2 vs. 6.6%, respectively) [$F_1(1,21) = 35.38$, $MS_e = 22.70$; $F_2(1,98) = 10.51$, $MS_e = 173.65$]. However, the ANOVAs on the mean RT data did not show any pseudoword frequency effect (less than 3 msec, both $ps > .20$).

It is important to note that the obtained pseudoword frequency effect (at the .1 quantile and in the error data) was not due to the fact that low-frequency pseudowords did not activate their corresponding base words: Low-frequency pseudowords generated more false positive errors and longer RTs than the distant pseudowords [error rates, 6.6 vs. 2.6%, respectively; $F_1(1,21) = 26.40$, $MS_e = 6.67$; $F_2(1,98) = 11.53$, $MS_e = 34.70$; .1 quantile, 658 vs. 638 msec, respectively; $F_1(1,21) = 4.65$, $MS_e = 1{,}013.8$; $F_2(1,98) = 4.34$, $MS_e = 1{,}692.9$; mean RTs, 849 vs. 807 msec, respectively; $F_1(1,21) = 19.36$, $MS_e = 1{,}009.8$; $F_2(1,98) = 16.73$, $MS_e = 2{,}781.8$].

Word data. Again, the ANOVAs on the mean RTs showed a significant effect of word frequency [$F_1(1,21) = 242.33$, $MS_e = 402.4$; $F_2(1,148) = 49.16$, $MS_e = 2{,}646.5$]. The ANOVAs on the error data also showed a significant effect of word frequency [$F_1(1,21) = 40.69$, $MS_e = 14.54$; $F_2(1,148) = 49.16$, $MS_e = 31.02$].

As in Experiment 1, we found faster RTs to low- than to high-frequency pseudowords in the leading edge of the RT distribution. A substantial pseudoword frequency effect (i.e., more errors to high-frequency pseudowords) was also found in the error data. Taken together, these results are consistent with the models that predict that high-frequency pseudowords generate more lexical activation in the early stages of word recognition than do low-frequency pseudowords (e.g., the DRC model and the MROM). As in Experiment 1, the pseudoword frequency effect disappeared in the bulk of the distribution (the effect was 2 msec in the mean RTs; the median RTs showed virtually the same values for high- and low-frequency pseudowords: 833 msec in both cases).

As in Experiment 1, the pseudoword frequency effect with RL pseudowords occurred in the leading edge of the RT distributions (a robust 25-msec effect at the .1 quantile), but it disappeared in the bulk of the RT distributions. This pattern of results suggests that there may be two opposite processes at play for "no" responses with RL pseudowords. On the one hand, fast responses to pseudowords may be adjusted by a deadline mechanism that depends on global activation in the lexicon in the early stages of word processing. This mechanism is reflected both in the leading edge of the RT distributions (i.e., faster "no" responses to low-frequency pseudowords) and in the presence of substantially more "yes" responses to high-frequency pseudowords (i.e., activation reaches the threshold for "yes" responses more frequently for high-frequency pseudowords; see Coltheart et al., 2001; Grainger & Jacobs, 1996). Consistent with this interpretation, mean error RTs for RL high-frequency pseudowords were substantially lower than the mean error RTs for RL low-frequency pseudowords (651 vs. 898 msec; indeed, *all* participants showed this pattern). In other words, in the early stages of word recognition, RL high-frequency pseudowords produced a higher level of activation in a "wordness" dimension compared with the RL low-frequency pseudowords.

On the other hand, as we said in the introduction, slow responses to pseudowords may be the result of a (slower) verification process that causes the reset of activation of the corresponding base words. The basic assumption here is that low-frequency items may need more time to be verified than high-frequency items (Paap et al., 1982; see also O'Connor & Forster, 1981). This would imply that, in a standard yes/no lexical decision task, the word unit activated in a first stage by a RL high-frequency pseudoword may be deactivated from the "candidate set" during processing—once this unit has been verified and a discrepancy (e.g., a mismatching letter) with the stimulus item has been found. That is, the units corresponding to high-frequency words would be no longer active in

Table 4
Mean Lexical Decision Response Times (in Milliseconds), Response Times at the .1 Quantile (Q), and Percent Errors (PE) for the Pseudoword Targets in Experiments 3 and 4

	Pseudoword Category									Difference Score (HF − LF)		
	RL LF			RL HF			RL Control					
	M	Q	PE	*M*	Q	PE	*M*	Q	PE	*M*	Q	PE
Experiment 3 (yes/no)	849	658	6.6	851	683	15.2	807	638	2.6	2	25	8.6
Experiment 4 (go/no-go)	921	712	2.7	883	700	4.1	897	703	3.2	−38	−12	1.4

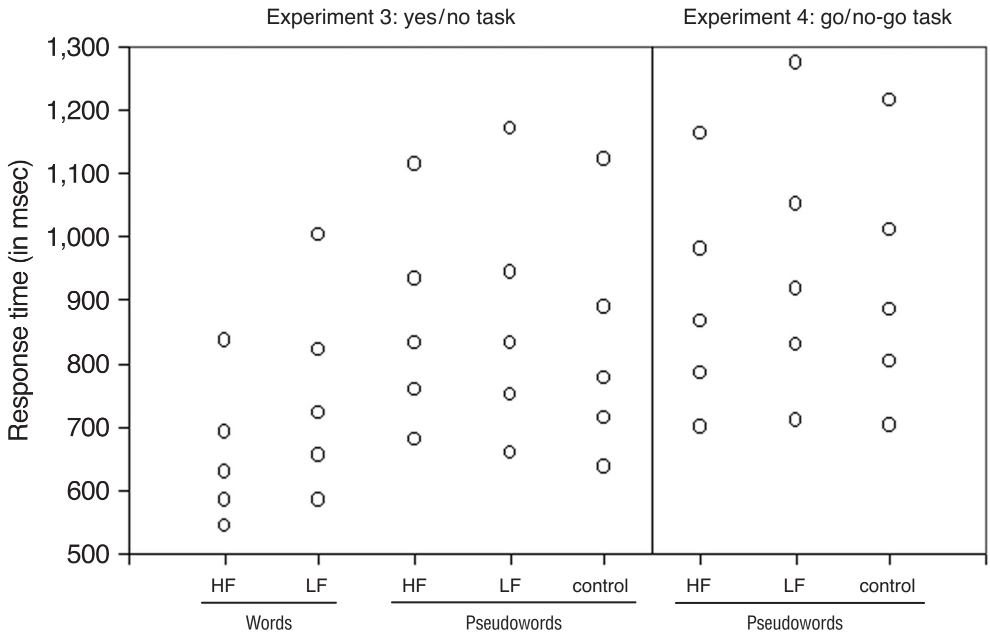

Figure 2. Group RT distributions for correct responses to word and pseudoword stimuli in Experiments 3 and 4. As in Figure 1, the circles represent the .1, .3, .5, .7, and .9 quantiles for a given stimulus type. HF, LF: high- and low-frequency words, respectively.

the word recognition system later in processing. If this interpretation is correct, low-frequency pseudowords may have longer RTs than high-frequency pseudowords at the higher quantiles. Indeed, if we look at the tail of the RT distributions (.9 quantile), latencies to RL high-frequency pseudowords are *faster* than the latencies to RL low-frequency pseudowords (56 msec) [$F_1(1,21) = 3.21$, $MS_e = 10,814.3$, $p = .088$; $F_2(1,98) = 0.85$, $MS_e = 41,165.2$]. What we should also note is that the .9 quantile is quite similar for the RL high-frequency pseudowords and the distant pseudowords (Figure 2): This is again consistent with the view that the lexical unit corresponding to the base word of the high-frequency pseudowords may have been deactivated during processing.

But how can we test the presence of this alleged "verification" (or postaccess matching) process? One way to test this proposal with the lexical decision task is to run a go/no-go task with pseudoword responses (i.e., in this task, participants have to respond to pseudowords and refrain to respond to words; see Perea et al., 2002, for review). Experiment 4 is a go/no-go replication of Experiment 3. In the go/no-go task with pseudoword responses, if the lexical entry of a high-frequency word is verified earlier than the lexical entry of a low-frequency word (e.g., Paap et al., 1982), we should obtain faster latencies to RL high-frequency pseudowords than to RL low-frequency pseudowords. (Note that our stimuli are eight-letters long and in embedded in sparse neighborhoods; in high-density neighborhoods, the predictions are more complicated since there may be other word units that are activated by the pseudoword.[4]) In contrast, the global activation in the lexicon generated by the pseudowords will presumably play a minor role in the detection of RL high- or low-frequency pseudowords (i.e., there won't be a response criterion for "yes" responses). More specifically, a "go" response is presumably made when no word units are active in the lexical system: If the base word of the high-frequency pseudowords is deactivated earlier than the base word of the low-frequency pseudowords, we should obtain faster RTs for high- than for low-frequency pseudowords. Evidence that the low-frequency word was activated by its corresponding pseudowords would be provided by slower classification of these pseudowords compared with distant, control pseudowords.

Finally, we should note that the Experiment 4 resembles closely the misspelling detection task used by O'Connor and Forster (1981, Experiment 3). O'Connor and Forster used a yes/no lexical decision task in which the participants were required to decide as quickly as possible whether the presented string of letters was a misspelled word or not. (That is, both words [e.g., *MOTHER*] and distant pseudowords [e.g., *NORDLE*] required a "no" response, whereas misspelled words [e.g., *MOHTER*] required a "yes" response.) Under these instructions, they found that TL high-frequency pseudowords had substantially shorter latencies than the TL low-frequency pseudowords (e.g., *MOHTER* vs. *BOHTER*; 1,258 vs. 1,454 msec, respectively), whereas the opposite was the case with the standard lexical decision instructions (696 vs. 678 msec; O'Connor & Forster, 1981, Experiment 1). The results of

O'Connor and Forster with the misspelling detection task suggest that participants verify the high-frequency entries in the lexicon earlier than the low-frequency entries. Thus, this finding reinforces our prediction that latencies for RL high-frequency pseudowords will be shorter than the latencies for RL low-frequency pseudowords. We decided to use the go/no-go task rather than the misspelling detection task because it is presumably simpler than the misspelling task; bear in mind that the latter task may represent a difficult challenge for the participants: It produces very long RTs (over 1,200–1,500 msec in the O'Connor & Forster, 1981, study) and a high error rate (15%–25% in some conditions).

It can be argued that the go/no-go task with "nonword" responses is not particularly ecological and hence may not be a good tool to support inferences regarding the role played by verification processes in lexical decision (and normal reading). Nonetheless, we believe that this task may offer an important window to verification/post-access processes, since it provides a signal that processing of a word has failed, and hence it may serve a useful function in the process of visual word recognition (see Kinoshita, Taft, & Taplin, 1985).

EXPERIMENT 4

Method

Participants. Twenty-five psychology students from the University of Valencia took part in the experiment for course credit. All of them had either normal or corrected-to-normal vision and were native speakers of Spanish. None of them had taken part in the previous experiments.

Materials and Design. The materials and design were the same as in Experiment 3.

Procedure. The procedure was the same as in the previous experiments, except that participants were instructed to press a key if the letter string was not a Spanish word and refrain from responding if the letter string was a Spanish word. On each trial, the stimulus remained on the computer screen until the participant responded or until 2 sec had elapsed (e.g., see Perea et al., 2002).

Results and Discussion

Lexical decision latencies less of than 250 msec or greater than 1,500 msec (less than 4.5%) were excluded from the mean RT analyses. The mean RT, the .1 quantile, and percent error from the subject analysis are presented in Tables 2 and 4. Figure 2 shows the five quantiles for responses to the stimuli.

Pseudoword data. The ANOVAs on the leading edge of the RT distributions (.1 quantile) showed that, on average, high-frequency pseudowords had slightly faster latencies than did low-frequency pseudowords (700 vs. 712 msec, respectively), but this difference was not statistically significant [$F_1(1,24) = 1.62$, $MS_e = 1,045.8$, $p > .10$; $F_2(1,98) = 3.51$, $MS_e = 3,788.5$, $p = .064$]. The ANOVAs on the mean RT data showed that high-frequency pseudowords had substantially faster latencies than did low-frequency pseudowords (883 vs. 921 msec, respectively) [$F_1(1,24) = 16.38$, $MS_e = 1,128.7$; $F_2(1,98) = 6.23$, $MS_e = 3,793.2$].

The ANOVA on the error rates failed to show a difference between high- and low-frequency pseudowords (both ps $> .15$).

As in the previous experiments, it is important to note that the obtained pseudoword frequency effect (in the mean RT data) was not due to the fact that low-frequency pseudowords did not activate their corresponding base words: On average, responses to distant pseudowords had faster latencies than did responses to low-frequency pseudowords in the mean RT analysis (883 vs. 897 msec) [$F_1(1,24) = 5.45$, $MS_e = 1,336.8$; $F_2(1,98) = 5.64$, $MS_e = 2,892.6$]; this difference was not significant at the .1 quantile (700 vs. 703 msec).

Word data. The ANOVAs on the error data showed a significant effect of word frequency [$F_1(1,24) = 18.61$, $MS_e = 8.07$; $F_2(1,148) = 25.63$, $MS_e = 17.59$]. As predicted, we found faster RTs to high- than to low-frequency pseudowords, providing empirical support to the view that a verification process may play a role in discriminating pseudowords from words (see O'Connor & Forster, 1981, for a similar result with a misspelling lexical decision task). It is worth noting that this effect does not seem to occur very early in processing, as deduced by lack of a significant effect in the leading edge of the RT distribution (.1 quantile). Nonetheless, the difference between low- and high-frequency pseudowords was quite robust in the bulk of the RT distribution and in the higher quantiles (54, 72, and 111 msec, at the .5, .7, and .9 quantiles, respectively; see Figure 2).

Furthermore, as in the previous experiments, we found evidence that the base words corresponding to low-frequency pseudowords were indeed activated: Mean RTs were substantially lower for the control, distant pseudowords than for the low-frequency pseudowords.

GENERAL DISCUSSION

The present results have important implications for models of visual word recognition and lexical decision. The main findings can be summarized as follows: (1) Latencies to RL low-frequency pseudowords in the yes/no lexical decision task are shorter than the latencies to the RL high-frequency pseudowords in the leading edge of the RT distribution, but not in the bulk of the RT distribution (i.e., the mean or median RTs) (Experiments 1 and 3); (2) latencies to TL low-frequency pseudowords in the yes/no task are shorter than the latencies to the TL high-frequency pseudowords, both in the leading edge of the RT distribution and in central tendency measures (Experiment 2); and (3) the lexical entries of high-frequency words can be verified earlier than the lexical entries of low-frequency words, as deduced from the go/no-go task with "pseudoword" responses (Experiment 4).

Given that the pseudoword frequency effect is more robust for TL pseudowords than for RL pseudowords, we first discuss the issue of the choice of a coding scheme in models of visual word recognition. Next, we examine in detail the pseudoword frequency effect and its implications for the time course of lexical activation in models of visual word recognition.

The Choice of a Coding Scheme

The less robust effect of pseudoword frequency for RL than for TL pseudowords is in line with the view that RL pseudowords (i.e., BUDRET) may not be as perceptually similar to their base word (BUDGET) as TL pseudowords (BUGDET) (see Davis, 1999; Perea & Lupker, 2003a, 2003b, for review). Indeed, as found in Experiment 1, TL high-frequency pseudowords produced substantially more errors than RL high-frequency pseudowords (38% vs. 18.5%, respectively) when the items were presented briefly and masked, despite the fact that the TL pseudowords had fewer word neighbors and a number of the TL pseudowords had infrequent bigrams. Similarly, in the signal-to-respond paradigm (see Hintzman & Curran, 1997, for an application of this paradigm to lexical decision), Gómez, Perea, and Ratcliff (2002) found that participants made more false alarms to TL high-frequency pseudowords (e.g., BUGDET) than to RL high-frequency pseudowords (e.g., BUDRET) when the lag between the stimulus and the signal to respond was very brief (e.g., 100 or 200 msec). Further, Andrews (1996) found that the influence of TL word neighbors in the process of visual word recognition was inhibitory (e.g., TRIAL inhibits the processing of TRAIL), whereas the influence of RL word neighbors tended to be facilitative (e.g., TRAIN facilitates the processing of TRAIL).

Taken together, the above-cited findings pose problems for the coding scheme currently employed in the DRC model and in the MROM. In these two models, letters are assumed to be immediately tagged to their positions in the orthographic representation of the presented word (as in the original interactive activation model; see Rumelhart & McClelland, 1982). Thus, the TL pseudoword CAISNO would be clearly less similar to CASINO than the RL pseudoword CASIRO, and hence any pseudoword frequency effects should be greater for RL pseudowords than for the (distant) TL pseudowords. It is important to note, however, that Rumelhart and McClelland acknowledged that there might be a problem with the "position-specific" coding scheme in their model. Specifically, Rumelhart and McClelland suggested that "perhaps there is a region of uncertainty associated with each feature and with each letter" (p. 89). If this coding scheme were implemented, partial activation of letters from nearby positions would arise in a particular position along with the activation for the letter actually presented. Therefore, this new coding scheme would presumably capture the fact that TL pseudowords are more orthographically similar to their base words than are RL pseudowords (see Perea, Gómez, & Ratcliff, 2003, for an implementation of such a model). Recently, a number of alternative coding schemes have been proposed that can cope with the presence of TL similarity effects in a more direct way (e.g., the SOLAR model, Davis, 1999; the SERIOL model, Whitney, 2001). A discussion of these models would be beyond the scope of the present paper (see Perea & Lupker, 2003a, 2003b, 2004, for extensive discussion of these models), although we would like to note that in the SOLAR and SERIOL models, the TL pseudoword JUGDE is more similar to its base word (JUDGE) than to the RL-pseudoword JUDPE.

In sum, the coding scheme for word representations is not a trivial issue, and modelers should try to motivate their choice. In most models, the assumptions about how letter positions are coded are often made somewhat arbitrarily and without much empirical grounding (see Andrews, 1996; Perea & Lupker, 2003a). Nonetheless, these assumptions are critical to the success or failure of the models because they determine which words are considered similar and, therefore, which word representations are most likely to be activated by a particular string of letters.

The Frequency Effect for Pseudowords

Leaving aside the issue of the coding scheme, high-frequency pseudowords in the MROM or the DRC model generate more lexical activity than low-frequency pseudowords, and hence the temporal deadline for "no" responses is predicted to be set longer for high- than for low-frequency pseudowords. For instance, the summed lexical activation values after seven processing cycles with the MROM for the RL high- and low-frequency pseudowords were 0.32 versus 0.26 in the materials of Experiment 1, and .43 versus .38 in the materials of Experiments 3–4. Indeed, the DRC model and the MROM can readily accommodate the longer latencies of the high-frequency pseudowords relative to the low-frequency pseudowords in the leading edge of the RT distributions in the yes/no lexical decision task (Experiments 1–3).[5] However, the effect of pseudoword frequency on mean RTs appeared with TL pseudowords (Experiment 2), but not with RL pseudowords (Experiments 1 and 3). (Bear in mind that TL pseudowords seem to be more perceptually similar to their base words than do RL pseudowords.)

The pseudoword frequency effect for RL pseudowords in the leading edge of the RT distribution in the yes/no lexical decision task (i.e., faster RTs for low- than for high-frequency pseudowords) vanished in the bulk of the RT distribution (Experiments 1 and 3). The disappearance of the pseudoword frequency effect in the higher quantiles is not predicted by the DRC model or the MROM: That is, in these models, high-frequency pseudowords show a consistent advantage in terms of summed lexical activation over low-frequency pseudowords across number of cycles, and hence the deadline should be set longer for the high-frequency pseudowords across quantiles. The reason why the pseudoword frequency disappears is that a number of "no" responses in a lexical decision task may be based not only on lexical activation, but also on a later, verification (or postaccess matching), process (see Kinoshita et al., 1985; O'Connor & Forster, 1981; Paap et al., 1982). If lexical decision responses are made via this verification mechanism, the units corresponding to high-frequency words can be verified earlier than the units corresponding to low-frequency words. Consistent with this view, we found a robust facilitative effect of pseudoword frequency for RL pseudowords in the go/no-go lexical decision task with "nonword" responses (i.e., faster RTs for high- than for low-frequency pseudowords).

Taken together, these findings suggest that lexical activation in the internal lexicon is a dynamic process in which when an RL high-frequency pseudoword frequency is presented (e.g., UNIDED), it generates a high level of activity in the early stages of processing. (This is well captured by the number of false positives and the RT data at the .1 quantile.) However, once the lexical entry is (correctly) verified and a mismatch is found, the lexical entry is deactivated, and hence the activation produced by RL high-frequency pseudowords is reduced later in processing. This interpretation is consistent with the fact that at the higher quantiles, the RT distribution of the RL high-frequency pseudowords mimics the RT distribution of the distant pseudowords (Figure 2). Of course, one might wonder why this interpretation does not apply to TL pseudowords as well. The reason is that there is a difference between the two types of pseudowords (see previous section): The divergence between a pseudoword and its base word is more noticeable in the case of RL pseudowords than of TL pseudowords, and hence the verification process is more likely to detect a mismatch in the case of RL pseudowords. Bear in mind that, unlike RL pseudowords, TL pseudowords share *all* the letters with the base word.

The proposal of a verification process in the context of the lexical decision task is not new. For instance, Bourassa and Besner (1998) found a significant associative priming effect with nonword primes (e.g., *judpe*– COURT) when the primes were presented briefly and masked, but not when the primes were visible. Bourassa and Besner argued that the unit corresponding to the prime (e.g., *judpe*) at target processing would be active when the lexical entry corresponding to the prime had not been verified (masked priming), but not when the lexical entry had been verified (unmasked priming). Recently, Ziegler, Jacobs, and Klüppel (2001) reported that lexical decision responses to pseudohomophones whose base word was of high frequency were faster and more accurate than the responses to pseudohomophones whose base word was of low frequency. Ziegler et al. argued that an active verification process (rather than a temporal deadline) could explain this effect. (Ziegler et al. did not examine the RT distributions; however, if our reasoning is correct, the facilitative effect of pseudohomophone frequency would increase in the higher quantiles.)

It is important to stress that the postulated verification mechanism is likely to occur during normal reading, rather than just being a specific mechanism to make lexical decisions. The verification process is probably a general process concerned with the verification of hypotheses about the identity of the stimulus (see Paap et al., 1982; Paap & Johansen, 1994). As Kinoshita et al. (1985; see also Ziegler et al., 2001) argued, a verification/postaccess mechanism may serve a useful function in normal reading, since it may signal that word identification has failed (e.g., a "go" response in a go/no-go lexical decision task). For instance, Pollatsek, Perea, and Binder (1999; Perea & Pollatsek, 1998) found that during normal reading, words with higher frequency neighbors had more regressions (e.g., *spice*, because of its higher frequency neighbor *space*)—and longer fixations after leaving the target word (so-called *spillover* effects)—than words with no higher frequency neighbors. Pollatsek et al. argued that on a fraction of trials, the target word might have been misidentified as a higher frequency neighbor and then at some point the reader realized from the sentence context that the word was probably misidentified and needed to reencode the visual information. That is, these regression/spillover effects may well be a by-product of verification/postaccess processes that occur in normal reading (and in the lexical decision task). We must bear in mind that the average participant is not used to reading nonwords—or to performing lexical decisions—in her/his daily life, and he/she may well take into account some information/clues used in normal reading.

More empirical/theoretical work is necessary to examine in detail how a verification account can be used in conjunction with an activation-based account to produce "no" responses in a lexical decision task. One important issue is how an activation-based model can deactivate the "rejected" high-frequency word units from the candidate set quickly enough without violating the spirit of these types of models (i.e., in a "homunculus-free cognitive system"; see Grainger, 2000). As Forster (1994) pointed out, it is possible to postulate a postdischarge orthographic checking mechanism via a "cleanup" network in a connectionist model (also see Kwantes & Mewhort, 1999, for the implementation of a verification stage in an activation-based model). This additional system would compare the stimulus with the orthographic specification appropriate for the preselected representation. If the check reveals a mismatch, the identification process resumes and the activation of the node corresponding to the high-frequency word would be deactivated; otherwise the response would be "yes." If no "yes" response has been produced by the time some adjustable temporal deadline is reached, the response would be "no" (see Forster, 1994). One other possibility would be to consider adaptive resonance theory networks (see Carpenter & Grossberg, 1987; Grossberg & Stone, 1986; Stone & Van Orden, 1994). In these networks, lexical representations are "functionally unitized" via a number of matching cycles until the system reaches equilibrium (via bottom-up information and top-down expectations), so that both activation and verification processes would be seen as part of a single mechanism.

CONCLUSIONS

To summarize, the results of the present lexical decision experiments demonstrate that participants shift the deadline for "no" responses to pseudowords on the basis of the frequency of their base words, as predicted by the DRC model and the MROM. Although the presence of greater effects of pseudoword frequency for TL pseudowords than for RL pseudowords cannot be captured by the coding scheme currently used in the DRC model or the MROM, it may be accommodated by assuming a region of uncertainty associated with each letter (overlap model, Perea et al., 2003) or by using other recently proposed coding schemes (e.g., the SOLAR model, Davis, 1999; the SERIOL model, Whitney, 2001). Finally, the present study provides a clear demonstration of the utility of analysis of the RT distributions (also see Ratcliff, Gómez, & McKoon, 2004). If we had examined only the mean RTs, we would have missed the effect of frequency for RL pseudowords in the leading edge of the RT distributions.

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NOTES

1. It is worth noting that O'Connor and Forster (1981) argued that a search model would predict no frequency effect for pseudowords, at least for the error data, on the basis that the probability of a false identification would be essentially controlled by the similarity of the pseudoword to its base word.

2. In the above-cited papers, the pseudowords were created by replacing the final letter (Allen & Emerson, 1991; Allen et al., 1992), replacing the initial vowel (Arduino & Burani, 2004; den Heyer et al., 1988), replacing a randomly chosen vowel (Frederiksen & Kroll, 1976; Stanners et al., 1975), replacing a randomly chosen letter (Duchek & Neely, 1989; Grainger & Jacobs, 1996; Paap & Johansen, 1994), or by changing or omitting one or two letters from a word (Rajaram & Neely, 1992).

3. The untruncated mean RTs for the different conditions essentially paralleled the truncated mean RTs. Here is a link to the untruncated mean RTs: http://www.uv.es/~mperea/meanRT-PRG.PDF

4. The original activation-verification model would assume that the candidate set for low- and high-frequency pseudowords in a very sparse neighborhood consists of one word unit. As an anonymous reviewer pointed out, if there is only candidate, then the sole candidate will be verified first, because there are no other candidates, and thereby no frequency effect for pseudowords would be expected. Nonetheless, it is possible to assume a "risky" verification strategy in which a near match to a familiar word is used as a basis for responding "no" in a standard lexical decision task or "go" in a task that requires the detection of a mispronunciation/misspelling. This modified activation-verification account would predict faster "go" responses for high- than for low-frequency pseudowords in the present experiment.

5. Nonetheless, increasing the number of high-frequency word neighbors may facilitate responses to pseudoword stimuli (Grainger & Jacobs, 1996): Pseudowords with several high-frequency word neighbors will generate a lower level of lexical activation in early stages of word processing—because of lexical inhibition at the lexical level—than pseudowords with no high-frequency word neighbors, and thereby the temporal deadline for responding "no" will be set higher.

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