Journal of Memory and Language **42,** 342–364 (2000)
doi:10.1006/jmla.1999.2687, available online at http://www.idealibrary.com on IDEAL®

Lexical and Nonlexical Print-to-Sound Translation of Disyllabic Words and Nonwords

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Almost all of the theoretical and empirical work on reading aloud has considered only the reading of monosyllables, and so the special problems which arise when one is attempting to give an account of how polysyllabic words and nonwords are read aloud have been thoroughly neglected. Here we begin to remedy this neglect with an exploratory study of this issue from the viewpoint of the dual-route theory of reading. We propose an explicit set of nonlexical rules for the orthographic–phonological translation of disyllabic letter strings which includes procedures for assigning stress and reducing vowels. We show that this set of rules predicts well how people assign stress to disyllabic nonwords and that the naming latencies for English disyllabic strings whose stress violates that predicted by these rules are longer than the latencies for words which obey these rules, especially when the words are low in frequency. We conclude with a consideration of how a particular dual-route computational model of reading, the DRC model, might be extended so as to account for these findings. © 2000 Academic Press

Key Words: reading aloud; stress assignment; dual-route model; regularity; nonwords; disyllables.

Research investigating the processes involved in print-to-sound translation has flourished over the past 25 years, yielding empirical data which have identified a number of variables that seem to figure heavily in this process (e.g., regularity, consistency, frequency). A number of theories of reading aloud which seek to explain these data have been developed, and these theories have grown increasingly specific with a heightened interest in realizing verbal theories as computational models. A number of computational models of reading aloud are currently being studied (e.g., Coltheart, Curtis, Atkins, & Haller, 1993; Plaut, McClelland, Seidenberg, & Patterson, 1996; Zorzi, Houghton, & Butterworth, 1998).

Virtually all of this theoretical, empirical, and computational modeling work has focused on the print-to-sound translation of monosyllabic words and nonwords. Only a few authors (e.g., Humphreys & Evett, 1985; Patterson & Morton, 1985) have acknowledged the theoretical difficulties encountered when the phonological recoding of printed polysyllables is considered. Focusing exclusively on the monosyllable allows reading theorists to avoid discussing the procedures by which stress assignment and vowel reduction might be accomplished as words and nonwords are read aloud. Although this simplification has allowed a number of successes in modeling the reading aloud of mono-

This work was supported by an NSF Graduate Research Fellowship awarded to the first author, an ARC Special Investigator Grant awarded to Max Coltheart, and an MRC Programme Grant awarded to Lorraine K. Tyler and William Marslen-Wilson. We are grateful to Steve Saunders and Breck Thomas for programming assistance and are indebted to Jonathan Harrington, Michael Kelly, Jo Ziegler, Marco Zorzi, and two anonymous reviewers for thoughtful comments on an earlier version of this paper.

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0749-596X/00 $35.00

syllables, any theory or model with aspirations to completeness will sooner or later have to confront the problems which arise when polysyllables are considered.[1] In this work, we begin to consider how these problems might be addressed by one theory of reading in particular, the dual-route theory (e.g., Coltheart, 1978; Forster & Chambers, 1973; Patterson & Morton, 1985; Patterson & Shewell, 1987). We further try to relate our conclusions to a particular implementation of the dual-route theory, the DRC model (Coltheart et al., 1993; Coltheart & Rastle, 1994; Rastle & Coltheart, 1998, 1999a,b).

THE DUAL-ROUTE THEORY OF READING

The central tenet of the dual-route theory of reading is that two procedures are required for the correct print-to-sound translation of exception words and nonwords. While correct pronunciation of exception words requires a lexical lookup procedure, correct pronunciation of nonwords requires a nonlexical, rule-governed, procedure. Application of the nonlexical procedure to an exception word results in a regularization error (e.g., pronouncing PINT as if it rhymed with MINT), and similarly, application of the lexical procedure to a nonword results in a lexical capture (e.g, pronouncing STARN as START). Regular words can be read aloud by either procedure, though of course by different means.

Exception words are read aloud more slowly than regular words, according to the theory, because they generate conflicting information between lexical and nonlexical procedures, while regular words do not. The theory predicts an increase in the size of the exceptionality cost as word frequency decreases, as is the case in reading aloud (e.g., Paap & Noel, 1991; Seidenberg, Waters, Barnes, & Tanenhaus, 1984; but see Jared, 1997, who reported a consistency effect for high-frequency words), because (a) the size of the regularity effect is determined, in part, by the speed at which lexical information is activated relative to nonlexical information and (b) the speed at which lexical information is activated is determined, in part, by word frequency.

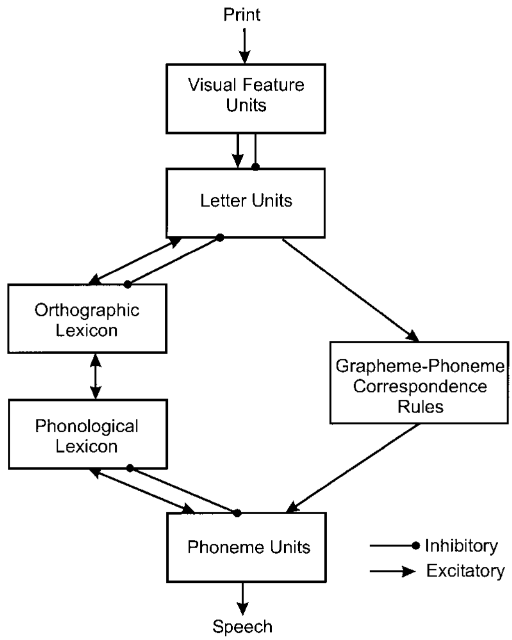

FIG. 1. The DRC model.

Coltheart and his colleagues (Coltheart et al., 1993; Coltheart & Rastle, 1994) sought to specify this theory of reading further by implementing it as a computational model, the DRC model. Its architecture is shown in Fig. 1, and has been described in detail by Coltheart and Rastle (1994) and Rastle and Coltheart (1998, 1999a,b).

As shown, the DRC model utilizes a lexical procedure and a nonlexical procedure for the nonsemantic translation of print to sound (a third procedure via a semantic system has not been implemented). These procedures share a feature identification system, a letter identification system, and a phoneme system. The lexical route houses orthographic and phonological entries for every monosyllable in English, and the nonlexical route operates by applying a set of

[1] Ans, Carbonnel, and Valdois (1998) have recently reported the development of a computational model of French polysyllabic word reading. However, the difficulty which arises in developing a computational model of English—namely, the placement of stress—does not arise in French, because French does not have lexical stress (see e.g., Beckman, 1986).

grapheme-to-phoneme correspondence (GPC) rules serially, letter by letter, across the item. Processing in the lexical route of the model is graded, cascaded, and fully interactive.

Coltheart and Rastle have reported a number of the model's successful simulations, including the regularity effect and its interaction with frequency and position of irregularity, the pseudohomophone effect and its modulation by base-word orthographic similarity, homophone priming, and the length effect in nonword reading. Simulation work on reading aloud by the model has so far been restricted to monosyllabic word and nonword reading because, although the nonlexical route can translate a polysyllabic item into a string of phonemes, it cannot assign stress or reduce vowels appropriately. Hence, pronunciations of polysyllabic letter strings cannot be exactly simulated by the present form of the model.

DUAL-ROUTE THEORY AND THE PROBLEM OF POLYSYLLABIC WORDS

If dual-route theory is to be extended beyond the monosyllabic domain, then the reading aloud of polysyllables, which requires stress assignment and vowel reduction, must be expressible as a function of lexical and nonlexical procedures. This task is easily accomplished as far as the lexical procedure is concerned; including polysyllabic words in an orthographic input lexicon and a phonological output lexicon poses no problems. However, polysyllabic words do pose special problems for the nonlexical procedure, specifically in explaining how this rule-based procedure, when translating polysyllabic items from print to sound, assigns stress and reduces vowels appropriately.

Whatever the means by which this might be done by rule, it seems certain that some English polysyllabic words would violate whatever rules for stress assignment and vowel reduction are used by the nonlexical route. One might thus expect that the reading aloud of stress-irregular words will be subject to an exceptionality cost, particularly if the words are of low frequency—just as for words with segmental irregularities. A system of nonlexical rules which describes procedures for stress assignment and vowel reduction is needed, however, in order to classify words as regular or irregular on the basis of their suprasegmental information.

Developing rule systems for these procedures has been a focus of linguistic research for many years (e.g., Baker & Smith, 1976; Baptista, 1984; Chomsky & Halle, 1968; Fudge, 1984; Liberman & Prince, 1977; Smith & Baker, 1976; Trammell, 1978; Williams, 1987). However, none of these rule systems is particularly suitable for the nonlexical component of a dual-route model. Much of this literature has been concerned with the assignment of suprasegmental information to a prespecified phonological representation, not an orthographic one. The rule system that we seek, however, is one that translates the orthographic representation of a polysyllabic word to a complete phonological representation, containing both segmental and suprasegmental information. It should be applicable to words and nonwords alike and so must make use only of the letters, graphemes, and phonemes in the item. Many of the rule systems considered previously in linguistic research have required information such as etymology and syntactic class and so are inappropriate for use with nonwords.

Whether such a nonlexical procedure for reading aloud English polysyllabic words can be developed at all is unclear. While generating segmental information for polysyllabic words seems a straightforward extension of our work in defining the relationship between orthography and phonology for monosyllables, the generation of suprasegmental information seems more challenging. Consider the following statements.

> . . . it having been generally held that [English word stress] follows no rules. (Kingdon, 1958, p.xii)

> In fact lexical knowledge is the only reliable source for stress assignment, for languages like Italian and English where stress is not predictable. (Colombo & Tabossi, 1992, p.322)

Given these views, how much of English stress assignment can be predicted by nonlexical rule? For the purposes of this initial investigation, we will consider this question only in relation to disyllabic items.

It turns out that English stress can be predicted to a large degree by applying just one very simple rule: assign first syllable stress to *all* disyllabic items. Approximately 83% of disyllabic English words are pronounced with first syllable stress (CELEX Lexical Database, Baayen, Piepenbrock, & van Rijn, 1993), and so the nonlexical procedure of assigning first syllable stress to every disyllabic item will produce stress assignment that is correct far above chance levels. Disyllabic words in English might then be considered regular if they are stressed on the initial syllable and irregular if they are stressed on the final syllable. This type of statistically based rule, according to which stress regularity is determined by a single fact about the distribution of stress patterns in the language, has been considered a number of times (e.g., Brown, Lupker, & Colombo, 1994; Colombo, 1992; Colombo & Tabossi, 1992; Monsell, Doyle, & Haggard, 1989). Some evidence already exists which suggests that readers appeal to this type of rule in reading aloud polysyllabic items.

Colombo (1992) used this type of rule in a demonstration of regularity effects in reading Italian polysyllabic words. Although there are no irregular monosyllabic words in Italian, there are irregular Italian polysyllabic words, because the application of stress in Italian is not governed solely by rule. While most Italian words are stressed on the penultimate syllable (e.g., tac 'china), approximately 30% are stressed on the antepenultimate syllable (e.g., 'mac china). Based on this distribution, Colombo (1992) reasoned that for three-syllable words, penultimate syllable stress can be thought of as regular, whereas antepenultimate stress can be thought of as irregular. On manipulating word frequency and stress regularity, Colombo (1992) found the standard regularity by frequency interaction. While the regularity manipulation did not affect high-frequency words, irregularly stressed words of low frequency were slowed compared with low-frequency regularly stressed words (see also Colombo, 1988, as cited in Colombo, 1991, for a similar experiment involving lexical decision in which a stress regularity by frequency interaction appeared in the error data but not in the latency data).

Monsell et al. (1989, Experiment 3), in their investigation of the locus of frequency effects, did a similar experiment in English. Because most disyllabic English words are pronounced with first syllable stress, Monsell et al. classified these words as regular and classified disyllabic words with second syllable stress as irregular. Their experiment dealt with three variables—word frequency, task type, and stress regularity. Of primary interest here is the effect of stress regularity and its interaction with frequency in the naming task. Although it appears from their Fig. 7 that there was an interaction between these variables in the predicted direction, neither the main effect of stress regularity nor the interaction between stress regularity and frequency reached significance by subjects and by items.[2]

Brown et al. (1994) also investigated the interaction of stress regularity and frequency (though not for the purposes outlined here) in an experiment in which they used the stimuli designed by Monsell et al. (1989). Unlike Monsell et al. (1989), they reported a main effect of stress regularity and a nearly significant interaction between stress regularity and frequency. Subjects read aloud stress-irregular words more slowly than stress-regular words, particularly when the words were of low frequency. Unfortunately, neither item analyses nor item data were reported, so it is not clear whether the effects they observed were produced by only a small set of items in the stimulus set, whether they could be generalized to a different set of items, or why they did not produce equivalent effects in the Monsell et al. (1989) study.

Thus, we designed a similar experiment to investigate whether the standard regularity by frequency interaction could be produced using a different set of English disyllabic items classified as stress regular or stress irregular based on the fact that most disyllabic items are given initial stress.

[2] We are grateful to Stephen Monsell for providing to us these data.

EXPERIMENT 1

If dual-route theory is to be extended to polysyllabic word reading, then stress regularity must be expressed by nonlexical rule. If regularity can be determined by examining the distribution of stress patterns in the language in this way, then final syllable stressed English words should show a cost of irregularity, and this cost should be greater for low-frequency words than for high-frequency words.

Method

Subjects. Subjects were 18 first-year Macquarie University psychology students. All had normal or corrected-to-normal vision and were native speakers of Australian-English. Subjects received an introductory course credit for their participation.

Stimuli and apparatus. One-hundred-twenty disyllabic words were selected from the MRC Psycholinguistic Database (Coltheart, 1981). Sixty of these words were stressed on the first syllable ("regular") and 60 were stressed on the final syllable ("irregular"). Sixty of the words had Kučera and Francis (1967) frequencies over 100 occurrences per million, and 60 of the words had frequencies between 1 and 10 per million. Word frequency and stress regularity were varied in this way so that in each of four cells of the design there were 30 disyllabic words. None of the words had irregular monosyllabic GPCs. The four lists of items were groupwise matched on number of letters and on neighborhood size. Stimuli are shown in Appendix A.

One-hundred-twenty nonwords were added as fillers in order to maximize use of the nonlexical route, thereby emphasizing the conflict for low-frequency irregularly stressed words. All nonwords were phonotactically legal.

Presentation of words and nonword fillers was controlled and randomized for each subject using the DMASTR software (Forster & Forster, 1990) on a 486 PC. Naming latencies were recorded with the use of a voice key headset that fit each subject's head to ensure that the microphone remained at a constant distance from the subject's mouth throughout the experiment.

TABLE 1

Naming Latency (ms) and Percentage of Error as Functions of Word Frequency and Stress Regularity by Subjects (Item Data in Parentheses)

	Low frequency	High frequency
Naming Latency		
"Irregular" stress	554 (553)	531 (531)
"Regular" stress	557 (557)	528 (529)
Percentage of error		
"Irregular" stress	3.5 (3.3)	0.4 (0.4)
"Regular" stress	4.1 (4.1)	0.4 (0.4)

Procedure. Subjects were seated approximately 16 in. from the monitor and fitted with the voice key headset. They were instructed to read aloud the words and nonwords as quickly and as accurately as possible. Subjects were given 10 practice trials and then named the 240 target and filler items. The experimenter recorded errors for word targets by hand.

Results

Reaction times for word targets were recorded and latencies for errors and spoiled trials (because of voice key failure) were discarded. All remaining reaction times were winsorized to the second standard deviation boundary. Complete item data are contained in Appendix A. Subject and item data are shown in Table 1.

Two separate ANOVAs were performed on the subject and the item data. Stress regularity and word frequency were treated as repeated factors in the subject analysis; both of these variables were treated as between-items factors in the item analysis.

Results showed a main effect of frequency, as high-frequency words were read aloud more quickly than low-frequency words, $F_1(1,17) = 7.46$, $p < .05$, $MSE = 1616.37$, $F_2(1,116) = 21.02$, $p < .0001$, $MSE = 893.37$. There was no effect of stress regularity, however, as initially stressed words were not named any faster than finally stressed words, $F_1(1,17) = .00$, n.s., $F_2(1,116) = .07$, n.s. Finally, there was no interaction between stress regularity and word frequency, as the effect of stress regularity was the same for low-frequency words as for high-frequency words, $F_1(1,17) = 1.43$, n.s., $F_2(1,116) = .25$, n.s.

Errors were analyzed in the same way as was reaction time. A main effect of word frequency emerged, $F_1(1,17) = 27.54$, $p < .0001$, $MSE = .00059$, $F_2(1,116) = 13.22$, $p < .0001$, $MSE = .817$, as there were more errors for low-frequency words than for high-frequency words. As in the latency analysis, there was no effect of stress regularity, $F_1(1,17) = .22$, n.s., $F_2(1,116) = .16$, n.s. Similarly, there was no interaction between word frequency and stress regularity, $F_1(1,17) = .17$, n.s., $F_2(1,116) = .16$, n.s.

Discussion

Neither the latency data nor the error data produced an effect of stress regularity or an interaction between word frequency and stress regularity. Thus, it appears that while the nonlexical rule based on a single statistical fact about the language leads to psychologically real classifications of stress regularity in Italian (Colombo, 1992), it does not lead to such classifications in English.[3] If stress assignment and vowel reduction procedures can be described within a rule system which translates the orthography of English disyllabic words to phonology, then these procedures must be accomplished by more complex rules than are used in Italian.

[3] It has been argued that initial stress is regular for nouns, while final stress is regular for verbs (e.g., Kelly & Bock, 1988). In this experiment, many of the second syllable stressed irregular items were verbs, which could be viewed as somewhat problematic; if second syllable stress is actually regular for these items, then any effect of regularity (as we have defined it in this experiment) may have been masked. To investigate whether this might be the case, we compared reaction times of those irregular (second syllable stressed) words which occur only as nouns relative to those irregular words which occur only as verbs. If second syllable stress is actually regular for verbs (and indeed is the cause of the null effect in this experiment), then we would expect to see significantly faster naming latencies for verbs than for nouns in this comparison. There is no such effect, however: reaction times for "irregular" nouns ($M = 552$) and verbs ($M = 547$) did not differ, $t(24) = .34$.

A SET OF NONLEXICAL RULES FOR READING DISYLLABIC WORDS AND NONWORDS ALOUD

As discussed, previous linguistic research has generally considered the problem of stress assignment with respect to a prespecified phonological representation. Thus, in designing a nonlexical procedure for reading aloud disyllabic items, we might first develop appropriate nonlexical rules for deriving a phonological representation from orthography and then develop a secondary procedure for assigning stress and reducing vowels from this phonological representation.

However, depending on the extent to which regularities in the mapping between orthography and the placement of stress can be identified, it may be possible to develop a single procedure which derives both a phonological representation and a stress marker from the orthographic string. Recently, Kelly, Morris, and Verrekia (1998) have tried to identify such regularities in the mapping between orthography and stress placement. They identified particular orthographic segments at the ends of disyllabic words which, they proposed, "mark" the placement of stress in either the first or second syllable. An item whose stress placement diverges from its "marked" stress is considered irregular; an item whose stress placement is consistent with its "marked" stress is considered regular. On manipulating regularity in this way, they found support for their hypotheses about orthographic patterns which mark stress placement: subjects read aloud items whose stress patterns were consistent with their markings more accurately and more quickly than those items whose stress patterns were not consistent with their markings (though this effect in the latency data was significant only in the by-participants analysis).

Here, we take a similar approach to the problem of stress assignment to that taken by Kelly et al. (1998), seeking to find regularities in the mapping between orthography and the placement of stress. However, our aims differ from theirs in two ways. First, we aim not only to develop hypotheses about the relationship between orthography and the placement of stress, but also to integrate these hypotheses into a model of nonlexical translation of orthography to phonology for disyllabic words and nonwords. Second, we aim to instantiate our hypotheses about these procedures in the form of a computational algorithm. Elsewhere, we have argued that the latter of these points is particularly desirable (see e.g., Coltheart, 1996; Rastle & Coltheart, 1999a; Coltheart, Rastle, Perry, Langdon, & Ziegler, in press), as implementing a theory in the form of a computer program ensures that the theory is complete (or else the program will not run), and enables concrete tests of theory sufficiency (whether the program behaves in the same way that people behave). Thus, we endeavored to develop an approach to reading disyllabic words and nonwords which was sufficiently specific to form the basis of the nonlexical component of a computational dual-route model.

The approach that we adopted in designing suitable rules for this nonlexical route is due largely to the work of Garde (1968) and the more recent work of Fudge (1984). Both of these authors took the view that certain orthographic patterns can be identified as morphemes, and these morphemes have the propensity to influence the placement of stress. We will identify orthographic patterns which serve as these stress-placing morphemes and integrate this identification procedure with print-to-sound translation and vowel reduction in an algorithm designed to carry out these tasks automatically. Our algorithm is shown in Fig. 2.

Following Fudge (1984), our approach to stress assignment and vowel reduction relies heavily upon the identification of affixes, a principle not inconsistent with a growing body of literature which suggests that affixes are treated somewhat differently from other, nonmorphemic, parts of the syllable (e.g., Laudanna, Burani, & Cermele, 1994; Marslen-Wilson, Tyler, Waksler, & Older, 1994; Taft & Forster, 1975). The algorithm contains a store of 54 prefixes and a store of 101 suffixes, identified as such by Fudge (1984). The affixes in each store are ordered and searched by length, so that the suffix -NESS will be identified before the suffix -ESS, for example, and the prefix AB- will be identified before the prefix A-. Of course, since this procedure functions without reference to a lexicon of root morphemes, some affixes will be identified in items that are actually monomorphemic (e.g., the “affix” -er will be identified in the word “corner”) and in nonword items (e.g., the “affix” -ness will be identified in the nonword “signess”).

The algorithm first searches the string for the presence of a prefix. A successful match in the prefix lexicon is not sufficient for the string to be considered prefixed, however. Each prefix carries with it special conditions (e.g., ar- must be followed by r) that must be met. In addition, each prefix must be followed by an orthographically existing bigram in the first two positions of a word (based on monosyllabic bigrams). Thus, items like RENGING, though they contain the common prefix RE-, are not considered prefixed by the algorithm since the bigram NG does not occur in the first two positions of any monosyllabic English word.

If these conditions are met, then the prefix pronunciation is obtained from the affix store and the remaining portion of the item is translated via the GPC rules used by the nonlexical route of the DRC model. Generally, then, the full pronunciation is assembled and the prefix is given nonstress. In many cases, the prefix pronunciation contains schwa.

Sometimes, however, this procedure results in an unpronounceable string, and these instances are dealt with by a final check before pronunciation. Consider the item APPLE. The algorithm matches the prefix AP- in the prefix lexicon; it satisfies the conditions that occur with that prefix (must be followed by P) and passes the orthographic legality test (PL is legal in the first two positions of a string). The nonlexical rules of the DRC model translate the remainder of the string as /pl/, making the E silent since it occurs at the end of the word. The resulting pronunciation is the illegal string /əpl’/. Thus, before pronouncing any item with a prefix, the algorithm checks the phoneme string for a phonotactically illegal bigram in the last two positions of the string (based on phonological bigrams which do not occur in the

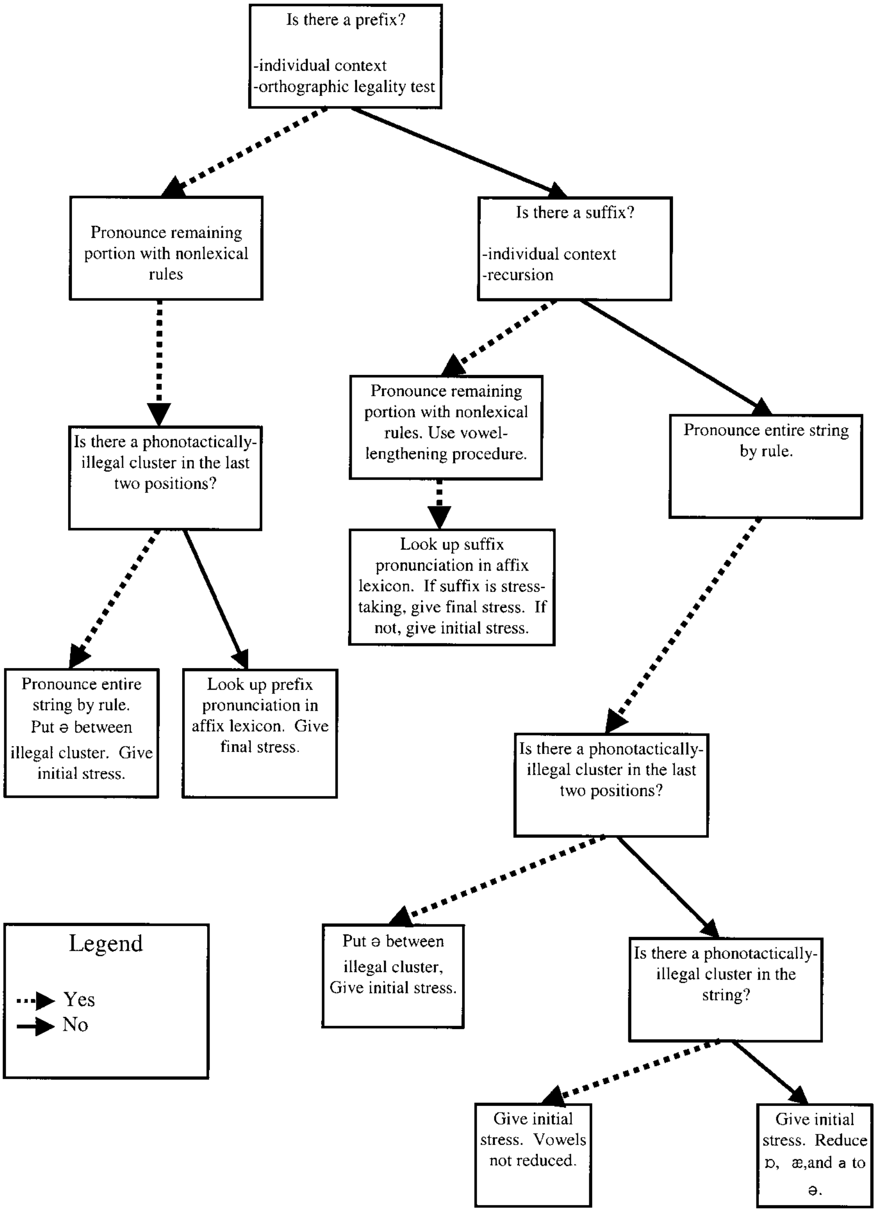

FIG. 2. The set of nonlexical stress rules.

final two positions of monosyllabic strings in English). If one occurs (as in əpl'), then the nonlexical rules of the DRC model are used to retranslate the entire string, ignoring the prefix, and a schwa is inserted between the illegal phonemes. In this case, the resulting pronunciation is correct: /'æpəl/.

If a prefix is not identified, the algorithm searches the end of the string for the presence of a suffix. Like each prefix, each suffix carries with it special conditions which must be met in order for it to be considered a suffix. There may be more than one suffix in an item (e.g., WEATHERED), and so a recursive identification procedure is built into the algorithm such that it searches the string until no more suffixes can be identified. When all suffixes have been identified, their pronunciations are obtained from the affix store and the remainder of the string is translated with the nonlexical rules used by the DRC model.

However, because the suffix has been stripped and translated by other means, the "root" of the item does not have access to a part of the word which may alter its pronunciation. Consider the item PRAVY. Here, the suffix Y is identified and the nonlexical rules used by the DRC model translate the remainder of the string as /præv/. The vowel here should be /eI/, however, not /æ/, because the presence of the Y lengthens the vowel. Thus, if the suffix closest to the "root" is Y or begins with E, and it is preceded by a single consonant letter, then if the first vowel is translated to /æ/, /ɒ/, or /ˆ/, it is lengthened to /eI/, /ou/, or /u/, respectively. In this case, the item is thus pronounced /'preIvi/. The suffix is then generally given nonstress unless it has been identified as a stress-taking suffix (e.g., -EEN, -IQUE, -OO), in which case it is given stress.[4] Many of the suffixes which do not take stress contain schwa.

If neither a prefix nor a suffix are identified, then the monosyllabic nonlexical rules contained in the DRC model are applied to the string and the item is given initial stress. Two checks then occur to determine whether the second phonological vowel is reduced to schwa. First, as was the case for prefixed items, the final two phonemes are examined for illegality. If these phonemes form a phonotactically illegal cluster, a schwa is inserted between them. If no such illegal cluster is present in the final two phonemes, the entire string is checked for phonotactic illegality (based on phonological bigrams which do not occur in any position in English monosyllables). If a phonotactically illegal cluster is identified, each vowel is given full value. If no such illegal cluster is identified, and if the second phonological vowel is /æ/, /ɒ/, or /a/, that vowel is reduced to schwa. The algorithm does not consider the placement of secondary stress.

[4] Following Fudge (1984), a number of word endings which are not strictly suffixes (e.g., -oo, -ique) have been included in the store of "stress-taking suffixes." Fudge (1984) notes that these word endings share the properties of stress-taking suffixes and account for the final stress assignment of many morphologically simple words.

TABLE 2

Correct Stress as a Function of Algorithm-Predicted Stress for All Disyllabic Words

	Algorithm prediction	
Correct stress	First	Second
First	17,903	1451
Second	945	2967

EVALUATING THE NONLEXICAL STRESS RULES

There are many ways in which the particular set of hypotheses we have advanced regarding the rules of nonlexical stress assignment could be evaluated. One way in which we might evaluate this set of hypotheses is to consider to what extent they capture regularities in stress assignment for the entire set of disyllabic words. That is, given the general principles we have adopted regarding the role of affix-like strings in the assignment of stress, what percentage of disyllabic words are stressed correctly by the algorithm? Each of the 23,266 disyllabic words contained in the CELEX database (e.g., Baayen et al., 1993) was submitted to the algorithm, and the resulting stress placement was identified. Table 2 shows the number of words given first and second syllable stress by the algorithm as a function of correct stress. As can be calculated from the table, the algorithm assigns stress correctly to 89.7% of all disyllabic words.

Evaluation of the algorithm also led us to discover facts about the relationship between orthography and grammatical class that we had not suspected previously. It has been suggested (e.g., Kelly & Bock, 1988) that first syllable stress is regular for nouns and second syllable stress is regular for verbs. Whether these claims are correct, any effects of grammatical class should certainly be dealt with in a lexical system, not a nonlexical system, since single nonwords do not carry information about grammat-

TABLE 3

Correct Stress as a Function of Algorithm-Predicted Stress for Nouns and Verbs Separately

	Algorithm prediction	
Correct stress	First	Second
Nouns		
First	5217	460
Second	198	189
Verbs		
First	266	18
Second	129	772

ical class. However, we used the algorithm to investigate whether information about grammatical class is in any way related to facts about orthography by submitting nouns and verbs separately to the algorithm and examining resulting stress assignment. We submitted the 6064 disyllabic words which are classed by the CELEX database solely as nouns and the 1185 disyllabic words which are classed solely as verbs to the algorithm and then examined the resulting stress pattern assignments. As shown in Table 3, when nouns were submitted to the algorithm, they were more likely to be stressed on the first syllable than on the second syllable; when verbs were submitted to the algorithm, they were more likely to be stressed on the second syllable than on the first syllable. Specifically, while a lexically based stress assignment rule such as "assign first syllable stress to nouns and second syllable stress to verbs" correctly stresses 90.74% of the 7249 nouns and verbs in Table 3, the nonlexical stress assignment procedure that we have described correctly stresses 85.6% of these words. Given these figures, one wonders how much of the apparent association between grammatical class and stress assignment can actually be accounted for by an association between orthographic properties and stress assignment (or, of course, an association between phonological properties and stress assignment, an issue which will be considered under General Discussion).

Although this set of hypotheses is quite successful in capturing regularities in the assignment of stress, it may be the case that this particular rule set holds no psychological reality—that these rules are not like the ones people use in assigning stress to single disyllabic words and nonwords. We thus carried out two additional experiments which aim to establish the extent to which this rule set provides a good description of the ways in which people assign stress to disyllabic words and nonwords.

EXPERIMENT 2

One way to evaluate the set of hypotheses advanced here is to investigate whether the way in which people assign stress to nonwords is related to the way in which our algorithm assigns stress to nonwords. Thus, in Experiment 2 we developed a set of nonwords which were submitted to the algorithm and then named by human subjects. Our intent was to compare the extent to which the placement of stress as determined by the algorithm for each item matched the placement of stress given by subjects.

Method

Subjects. Fifteen first-year psychology students from Macquarie University participated. All had normal or corrected-to-normal vision and were native Australian-English speakers. Subjects received course credit for their participation.

Materials and apparatus. Two-hundred-ten nonwords were constructed. All nonwords were phonotactically legal and were judged by both authors and the algorithm to be disyllabic. Seventy-six of the nonwords received second syllable stress by the algorithm. They received such stress because of the presence of a prefix or because of the presence of a stress-taking suffix. The other 134 nonwords received first syllable stress by the algorithm.

Stimulus presentation was controlled by the DMASTR software (Forster & Forster, 1990) running on a 486 PC. Responses were recorded on cassette tape.

Procedure. Subjects were seated approximately 16 in. from the display monitor. They were told that they would see a series of letter strings that did not form words, although they looked as if they could be words. They were told to pronounce each item as if it were a word, as accurately as possible, and were given 10 practice items.

The target stimuli were then presented one at a time, in a different random order for each subject. Because subjects were under no time pressure to respond, they controlled the pace of the experiment, pressing a button when ready for the next stimulus.

Results

Nonword pronunciation was recorded, and each response was coded as having stress on the first phonological vowel or on the second phonological vowel. Neither secondary stress nor vowel reduction were recorded. Because stress placement can affect vowel quality, the accuracy criterion used was quite liberal. The only instances in which a nonword stimulus was coded as an error were if the subject did not complete the utterance or if the pronunciation was not a reasonable approximation of that given by the monosyllabic rules of the DRC model. Because of the liberal scoring criterion, there were very few errors. Subject results were tallied, and each nonword was coded for the percentage of subjects that assigned initial stress and the percentage of subjects that assigned final stress. Item data are contained in Appendix B.

Two types of analysis were carried out to investigate whether subjects' assignment of stress was related to the stress assigned by the algorithm. First, χ^2 analyses, in which subject stress assignment was examined as a function of algorithm prediction, were conducted for each subject individually. Each of these analyses was highly significant (all *p*s $< .0001$), indicating a strong relationship between subject stress assignment and algorithm stress assignment, for each subject individually: $\chi^2_1(1) = 54.80$, $\chi^2_2(1) = 95.39$, $\chi^2_3(1) = 35.75$, $\chi^2_4(1) = 53.11$, $\chi^2_5(1) = 85.91$, $\chi^2_6(1) = 67.91$, $\chi^2_7(1) = 70.27$, $\chi^2_8(1) = 65.51$, $\chi^2_9(1) = 61.05$, $\chi^2_{10}(1) = 40.79$, $\chi^2_{11}(1) = 62.94$, $\chi^2_{12}(1) = 41.66$, $\chi^2_{13}(1) = 43.40$, $\chi^2_{14}(1) = 47.58$, $\chi^2_{15}(1) = 73.18$.

Second, we determined the modal subject stress pattern assignment for each item and then examined this as a function of the algorithm prediction (excluding those 4 items which did not have a modal stress assignment because of equivalent initial and final stress assignments). For those 130 items stressed on the initial syllable by the algorithm, the modal subject stress assignment was on the initial syllable for 105 of these items and on the final syllable for 25 of these items. For those 76 items stressed on the final syllable by the algorithm, the modal subject stress assignment was on the final syllable for 68 of these items and on the initial syllable for 8 of these items. Thus, the algorithm stress agreed with the modal subject stress for 84% of the items. The χ^2 analysis which tested whether algorithm stress and modal subject stress were independent was highly significant, $\chi^2(1) = 95.56$, $p < .001$, indicating a strong relationship between algorithm stress and subject stress.

Discussion

The analyses suggest that our algorithm captures at least some of the facts relevant to the ways in which people assign stress to nonwords. Unlike our original ideas about stress regularity—in which words stressed on the first syllable are considered regular—there seem to be a class of item that reliably takes second syllable stress. We suggest that this pattern of stress assignment may be related to the presence of morpheme-like orthographic segments—prefixes and stress-taking suffixes—which serve to place stress.

The construction of the nonlexical route of the current DRC model entailed the development of a set of hypotheses about the GPC rules people use in reading monosyllabic nonwords aloud. These hypotheses were intended to reflect how the majority of people pronounce any given monosyllabic nonword. Our goal was the same here—to design a set of hypotheses which pronounce disyllabic nonwords in the way that the majority of people pronounce these nonwords, complete with correct stress assignment and vowel reduction information. In examining the performance of the algorithm relative to human readers, however, it is clear that meeting this goal is still somewhat distant. While our algorithm captures many of the facts about stress assignment, it clearly does not capture all of the facts that people use when assigning stress to nonword items.

In order to investigate the areas in which the algorithm's performance was not like that of human readers, we calculated, for each item, the proportion of subjects who used, in their response, the same stress as the algorithm minus the proportion of subjects who used the opposite stress as the algorithm. Negative values (indicating disagreement between human readers and the algorithm) resulted for 33 (15.7%) of the items. Eighteen of these items (8.6%) had high negative values (over −.200): these are the items for which the algorithm fails.

Unfortunately, an examination of these items yielded few clues to the ways in which the algorithm is insufficient, though some patterns did emerge. All of the items for which the algorithm performs poorly are ones in which human readers assign second syllable stress and the algorithm assigns first syllable stress. Three of the items contain letter strings which form suffixes that reliably do not take stress: the items *cavance, datance,* and *kabist* contain suffixes which, in the set of disyllabic words, never take stress, yet subjects reliably assigned second syllable stress to these items. The items *gonnoze, dorrote, jinnife,* and *hennoke* have in common a short first syllable vowel and a long second syllable vowel; perhaps in the absence of affixes and illegal clusters, subjects assign stress to the syllable containing the long vowel. However, this rule fails to account for the fact that subjects in this experiment assigned first syllable stress to *wirtife.* The items *imream, emvoke, emage,* and *ilseeb* all contain letter strings which form prefixes, but the conditions required for these letter strings to be treated as prefixes by the algorithm are not met in these items, and hence they are given first syllable stress. Specifically, in the set of disyllabic words, IM- is a prefix only if followed by B, M, or P; EM is a prefix only if followed by B or P; and IL- is a prefix only if followed by L. So it seemed that readers may have overgeneralized the prefix rule. Two similar items, *ilgest* and *irsabe*, were also given unreliable stress by subjects (53 and 47% first syllable stress, respectively), though there are other items in which subjects seem to observe these constraints in prefix identification (e.g., *imwise* and *irsome,* which were given 67 and 100% first syllable stress, respectively). Thus, it seems clear that there are individual differences in the amount of information readers use in the identification of affixes; data which could elaborate this general observation are not available at present, however.

In general, this first attempt at developing an algorithm which translates orthography to phonology of disyllabic items by rule was reasonably successful in capturing some of the facts relevant to the ways in which readers assign stress to disyllabic items by rule. However, it is clear that we have not captured all of the relevant facts. Further empirical and modeling work will be required to discover what these facts are and how they might be reconciled with the system we have proposed.

EXPERIMENT 3

Our attempt in Experiment 1 to produce the stress regularity by frequency interaction in a set of disyllabic words failed: using a single rule based on the statistical distribution of stress patterns in the language failed to produce an effect of stress regularity in human readers. Thus, we developed a set of hypotheses that considers the types of facts which may be relevant to stress assignment and that seems to provide a reasonably good description of the ways in which people assign stress to nonwords. In Experiment 3, we investigated whether we would observe a main effect of stress regularity and/or a stress regularity by frequency interaction in word reading, using this set of hypotheses as the basis for the regularity classification.

As it turns out, when the algorithm we have proposed is applied to those items used in Experiment 1, the results show that 89% of the items are, in fact, classified as regularly stressed. Only three of the items in the "low-frequency irregularly stressed" condition of that experiment are classified as irregular by the algorithm; similarly, only three of the items in the "high-frequency irregularly stressed" condition are classified as irregular. Thus, our failure to observe a main effect of stress regularity or an interaction between stress regularity and frequency may have been due to the fact that nearly 90% of the items in that experiment were regular.

Therefore, an experiment similar to Experiment 1 was designed which measured naming latencies for words varied on stress regularity and frequency. If our hypotheses concerning the rules that human readers use to read disyllabic words aloud are correct, then we will find an effect of stress regularity. We further expect that this effect will be greater for low-frequency words than for high-frequency words.

Method

Subjects. Subjects were 26 Macquarie University psychology students. All subjects had normal or corrected-to-normal vision and were native speakers of Australian-English. Subjects received an introductory course credit for their participation.

Stimuli and apparatus. The algorithm described above was applied to several hundred words, from which 60 disyllabic words were selected as targets. According to the algorithm, each of these words was irregularly stressed, and none contained a GPC irregularity. Hence, stress regularity was isolated from other types of regularity in this experiment. If the algorithm identified a word as irregular only because of an irregular application of schwa (and not an irregular application of the stress marker), the word was not included in the experiment.

Kučera and Francis (1967) frequencies for each of these words were obtained, and the targets were split into a group of low-frequency words (frequencies below 25 per million) and a group of high-frequency words (frequencies above 50 per million). The algorithm indicated that very few words are stress irregular and GPC regular, and only a small percentage of these words are of high frequency; as such the high-frequency targets could not be separated from the low-frequency targets by as many frequency points as was desired. While 50 of the targets were of low frequency, only 10 were of high frequency.

Stress-regular controls were created for each group of targets. All of these controls were pronounced by the algorithm to ensure stress and GPC regularity. Irregular and regular items were groupwise matched on frequency, initial phoneme class (e.g., both fricatives), and word length.

Word presentation and data recording were controlled by the DMASTR software (Forster & Forster, 1990) running on a 486 PC. Responses were timed via a voice key which was attached to each subject's head so that the mouthpiece remained stationary throughout the experiment.

Procedure. Subjects were seated approximately 16 in. from the monitor and fitted with the voice key headset. They were instructed to read the words as quickly and as accurately as possible. Subjects participated in 10 practice trials and then named the 120 experimental trials. Trials were randomized for each subject. The experimenter recorded errors by hand during the session.

Results

Reaction times were collected and those for errors or spoiled trials were discarded. The item GUITAR was inadvertently classified as GPC regular, so this item was removed from the analysis. The item ANODE produced 77% errors (all of these were pure stress regularization errors), and so this item was also removed from the analysis. The remaining reaction times were winsorized to the second standard deviation boundary. Item data are contained in Appendix C.

Separate ANOVAs were performed on the subject and the item latency data. Subject analyses included two within-subjects factors (stress regularity and frequency); item analyses treated these two variables as between-items factors. Subject and item data are shown in Table 4.

The ANOVAs revealed a main effect of word frequency, $F_1(1,25) = 61.27$, $p < .01$, $MSE = 1037.37$, $F_2(1,114) = 41.16$, $p < .01$, $MSE = 952.56$, as naming latencies were longer for low-frequency items than for high-frequency items. A main effect of stress regularity also emerged, $F_1(1,25) = 17.41$, $p < .01$, $MSE = 290.37$, $F_2(1,114) = 18.38$, $p < .01$, $MSE = 952.56$, as naming latencies were longer for stress-irregular items than for stress-regular items. The cost of stress irregularity was greater for low-frequency words than for high-frequency words. This interaction be-

TABLE 4

Naming Latency and Percentage of Error as Functions of Word Frequency and Stress Regularity by Subjects (Item Data in Parentheses)

	Low frequency	High frequency
Naming latency		
Irregular stress	543 (545)	480 (481)
Regular stress	515 (516)	479 (479)
Percentage of error		
Irregular stress	15.50 (15.38)	1.70 (1.71)
Regular stress	1.10 (1.08)	0.00 (0.00)

tween stress regularity and frequency was significant by subjects, $F_1(1,25) = 22.12$, $p < .01$, $MSE = 208.78$, and there was a trend toward significance in the item data, $F_2(1,114) = 3.17$, $p = .078$, $MSE = 952.56$.

Error data were analyzed in the same way as were the latency data. Ninety percent of the errors were pure stress regularizations; the location of the stress marker was determined nonlexically. The other errors were a mélange of various mispronunciations. Most importantly, the ANOVAs revealed a stress regularity effect, $F_1(1,25) = 74.42$, $p < .01$, $MSE = .0024$, $F_2(1,114) = 27.87$, $p < .01$, $MSE = 159.65$, as there were more errors for stress irregular items than for stress regular items. Similarly, a frequency effect emerged, $F_1(1,25) = 102.22$, $p < .01$, $MSE = .0016$, $F_2(1,114) = 5.02$, $p < .05$, $MSE = 159.65$, as there were more errors for low-frequency items than for high-frequency items. The regularity effect was greater for low-frequency items than for high-frequency items, $F_1(1,25) = 83.73$, $p < .01$, $MSE = .0012$, $F_2(1,114) = 3.95$, $p < .05$, $MSE = 159.65$.

Eleven of the items in Experiment 3 had two possible stress patterns, though they were classified as regular or irregular based on the stress pattern of the highest frequency alternative. It could be argued that the conflicting lexical information about these items could result in slowed naming latencies; this possibility is especially worrisome since 9 of the 11 items were in the low-frequency irregular condition. Thus, we carried out additional analyses which excluded these items. The pattern of latency data was the same as that in the original analysis: an effect of frequency emerged, $F_1(1,25) = 66.12$, $p < .001$, $MSE = 920.53$, $F_2(1,103) = 38.41$, $p < .001$, $MSE = 906.43$; an effect of stress regularity emerged, $F_1(1,25) = 12.84$, $p < .01$, $MSE = 312.49$, $F_2(1,103) = 15.27$, $p < .001$, $MSE = 906.43$; and the interaction between these factors was significant by subjects, $F_1(1,25) = 20.91$, $p < .001$, $MSE = 176.75$, but not by items, $F_2(1,103) = 2.70$, $p = .10$, $MSE = 906.43$. Similarly, this error analysis showed an effect of frequency, $F_1(1,25) = 84.13$, $p < .001$, $MSE = .0016$, $F_2(1,103) = 4.48$, $p < .05$, $MSE = .0150$, an effect of stress regularity, $F_1(1,25) = 64.79$, $p < .001$, $MSE = .0028$, $F_2(1,103) = 26.44$, $p < .001$, $MSE = .0150$, and an interaction between these factors, $F_1(1,25) = 73.67$, $p < .001$, $MSE = .0012$, $F_2(1,103) = 3.79$, $p = .05$, $MSE = .0150$.

Discussion

In Experiment 1, we failed to find a main effect of stress regularity for low-frequency words or for high-frequency words when stress regularity was determined by a single fact about the statistical distribution of stress patterns in disyllabic English words. When stress regularity is classified on the basis of the set of hypotheses implemented in the algorithm we have described, a stress regularity effect does emerge, suggesting that the set of hypotheses presented here provides a good description of the knowledge to which human readers may appeal when reading disyllabic items aloud.

The effect of stress regularity was greater for low-frequency words than for high-frequency words, as is the case with GPC regularity. This effect was significant both by subjects and by items in the error analysis, although it only reached significance by subjects in the latency analysis. Because trends in the appropriate direction are evident in the mean naming latency values, it is likely that the small number of high-frequency stress irregular items contributed to the marginal significance in the item data. In addition, because of the high error rate for low-frequency irregularly stressed items, many of the items which may have produced slow naming latencies were removed from the analysis.

Thus, it appears as if disyllabic reading can be expressed within a dual-route theory and that the procedures described in Fig. 2 may capture some of the facts relevant to the ways in which people assign stress to words and nonwords.

GENERAL DISCUSSION

We have demonstrated that the procedures required for reading disyllabic items can be expressed in a system of rules and, moreover, that this set of hypotheses provides a good description of the rules to which human readers appeal, if, of course, they appeal to rules at all. Thus, it seems worthwhile to consider whether the principles on which this system of rules is based are consistent with a dual-route computational model of reading, the DRC model (Coltheart et al., 1993; Coltheart & Rastle, 1994; Rastle & Coltheart, 1998, 1999a,b), and if so, how that model might be expanded to accommodate the reading of disyllabic words.

Is This System Nonlexical?

One issue that must be considered immediately is whether the nonlexical rule system we have described in Fig. 2 runs contrary to the principles of the DRC model in its current nonlexical system. That is, would we have to relinquish our commitment to completely nonlexical processing on one side of the model in order to include a system which relies on a store of affixes? We think that the consequences of implementing such a system may not be this unfortunate and, in fact, believe that this system may fall within the principles of the current DRC model. Currently, the nonlexical route of the DRC model relies on rules which translate graphemes to phonemes. Thus, the nonlexical route already contains a store of graphemes—a store of instances in which letters combine to form graphemes. The nonlexical system described here contains this store and also a store of instances in which letters combine to form affixes. Of course, we concede that by including a store of morphological units in the nonlexical procedure, we have blurred somewhat the distinction between lexical and nonlexical information. Further thought is required to decide whether a store of letters which combine to form affixes and a store of letters which combine to form words are sufficiently distinct to refer to the former as “nonlexical” and the latter as “lexical.”

Complexity of the Nonlexical Rules

Another issue that should be considered is whether the nonlexical system that we have described is unnecessarily complex; could we sacrifice either the identification of prefixes or suffixes without cost to the system? We have explored this issue briefly by designing a second algorithm which eliminates the suffix identification procedure and comparing its performance to that of the full algorithm. Recall that of the 23,226 disyllabic words in the CELEX database, only 2396 were stressed incorrectly by the full algorithm. When the suffix identification procedure is removed entirely, the algorithm stresses 2489 words incorrectly: facts about the ends of words increase the performance of the model by only 93 words, a result possibly inconsistent with Kelly et al.’s (1998) claim that stress is “marked” at the ends of words. However, while the identification of suffixes does not seem to contribute substantially to stress assignment, this procedure is important for the correct assignment of phonology from orthography. Many of the suffixes identified by the full algorithm have pronunciations that contain lax vowels, despite having orthographies which normally correspond to tense vowels (e.g., IVE). Were these strings not identified as suffixes and given pronunications accordingly, they would be translated incorrectly. The *extent* to which the identification of suffixes plays a role in correct spelling–sound translation of polysyllables is an issue that requires further investigation, however.

Orthography or Phonology

Our algorithm seems to capture some regularities in the assignment of stress in disyllabic words using orthographic cues which often correspond to prefixes and suffixes. However, given the quasi-regularity of the orthography–phonology mapping in English, might it be the case that the cues critical to stress assignment are phonological rather than orthographic? Perhaps what readers do is to apply some form of grapheme–phoneme correspondence system to disyllabic letter strings and then assign stress on the basis of vowel quality. A regularity effect might then emerge for those items like ALLOY, which would be given second syllable stress by the algorithm due to the presence of a nonlexically translated lax vowel in the initial syllable. In order to proceed with a serious model of disyllabic word reading, we would have to determine empirically whether readers derive cues for stress assignment from orthographic or from phonological information.

Toward a Model of Disyllabic Reading

We have argued that the underlying principles of the algorithm described here are not fundamentally inconsistent with the principles on which the DRC model is based. Given this, how might the DRC model be extended to consider disyllabic word and nonword reading? The DRC model currently deals only with monosyllables, and hence its orthographic lexicon contains entries for all of the monosyllabic words in the CELEX database (Baayen et al., 1993)—7980 words in all—and the model's phonological lexicon contains entries for the pronunciations of all of these words. Extending the model so that it could deal with both monosyllables and disyllables would involve two things. First, the lexicons would need to contain entries for all of the monosyllabic and disyllabic words from the CELEX database: that would increase the size of the orthographic lexicon from 7980 words to 31,246 words. Since all of the entries in the orthographic lexicon have to be appropriately connected to the letter level and also to the phonological lexicon, and since all of the entries in the phonological lexicon have to be appropriately connected to the phoneme level and to the orthographic lexicon, this expansion would involve a large increase in the number of letter, phoneme, and word units and connections in the model. Because every unit in the model is updated on every processing cycle, and because such updating requires several computations for each connection in the model, this expanded DRC would run much more slowly, but that is merely a practical obstacle.

A more challenging aspect of adding stress to the operation of the lexical route would be to decide how and where lexical stress would be represented in the model: should there be separate levels for segmental (i.e., the component phonemes) and suprasegmental (i.e., the syllabic structure and position of stress) information in the lexical system? The most obvious way to include suprasegmental information in the lexical route of the DRC model is to include it within each lexical entry, so that, for example, the orthographic lexical entry for TRUSTEE would be connected to the phonological entry for /trˆsti'/. Representing suprasegmental information in this way would, however, run counter to many current speech production models which represent segmental and suprasegmental information separately (e.g., Butterworth, 1992; Levelt, 1992; Levelt, & Wheeldon, 1994) and may not capture many of the speech error and patient data which those models were intended to capture. Clearly, an explicit commitment to a particular hypothesis about the representation of suprasegmental phonological information will be required before the DRC model could be expanded to include disyllabic items. Compelling such commitments is, of course, one of the virtues of computational modeling.

The second modification to the model would be to replace its existing nonlexical route with a system like the one illustrated in Fig. 2, a system which includes the existing nonlexical grapheme-to-phoneme translation system but has procedures for dealing with stress assignment overlain upon it. Suprasegmental phonological information generated by this nonlexical system would need to be coordinated with suprasegmental phonology retrieved from the lexicon such that pronunciation latency is lengthened when there is conflict between these two sources of information.

Although we have suggested that stress assignment and vowel reduction can be explained within a dual-route theory, implementing this system of nonlexical rules into the DRC model will surely pose some major difficulties, some of which may be insoluble. We discuss one of these difficulties here. The set of hypotheses we have advanced regarding stress placement and vowel reduction by rule depends on information from all parts of the letter string, from beginning to end. However, the nonlexical route of the DRC model operates serially, from left to right, and we have argued previously (Coltheart & Rastle, 1994; Rastle & Coltheart, 1999a) that only early irregularities contribute to a latency cost in naming. Thus is it the case, then, that only the instances in which irregular stress becomes evident early in nonlexical processing will result in a latency cost in naming the item? Does this imply that irregularities in stress assignment derived from stress-taking suffixes are inconsequential to naming latency, given that this information is computed late in processing by the nonlexical system? Further experimental and modeling work is required to understand how the hypotheses we have advanced here can be reconciled with a serially operating nonlexical system.

Reading Polysyllables and Other Approaches to Reading

In the work presented here, we have considered whether, and if so how, the problem of polysyllabic words can be dealt with in a dual-route framework. In this pursuit, we have offered experimental work which shows that both segmental and suprasegmental phonological information can be generated by rule and, moreover, that classifications based on these rules predict human performance in reading aloud English words and nonwords to some degree, though clearly further experimental and modeling work is required before the present research can be reconciled with our previous modeling work in the monosyllabic domain.

While we have demonstrated that stress assignment can be predicted to some degree by a system of rules, the work we have presented here is not relevant to adjudicating between various approaches to modeling reading. On the contrary, the learning algorithm approach has proven to be an extremely popular and fruitful one in modeling reading aloud in the monosyllabic domain, in both dual-route frameworks (e.g., Zorzi et al., 1998) and single-route frameworks (e.g., Plaut et al., 1996; Seidenberg & McClelland, 1989), and may prove useful in dealing with the added complexities posed by polysyllabic words. One potentially desirable feature of this approach to defining relationships in quasi-regular domains is its ability to capture graded effects of consistency in the mapping of interest. Thus, these types of models could be seen as particularly suitable for the problem of stress assignment if it were demonstrated that gradations in the consistency of the mapping between orthography and stress assignment affected naming latency or accuracy. However, none of these models has considered the problem of English polysyllabic word reading. No doubt, as has been the case in our efforts with the DRC model, the special issues which arise when polysyllables are considered will pose these models some difficulty.

APPENDIX A

Item Data: Experiment 1

Word	RT	%Error
Low-frequency irregular targets		
abide	527	0.00
abyss	560	16.67
align	523	0.00
await	510	0.00
balloon	535	0.00
benign	575	0.00
brigade	604	0.00
cigar	552	0.00
deduce	552	0.00
disdain	608	0.00
disgust	579	0.00
dispel	556	5.56
disturb	550	0.00
forbid	575	5.56
imbibe	661	22.22
inept	540	5.56

Word	RT	%Error
lampoon	540	0.00
malign	569	0.00
maroon	525	16.67
ornate	537	5.56
pertain	541	0.00
platoon	544	5.56
restore	532	5.56
revolt	554	0.00
shampoo	520	0.00
suffice	536	16.67
trustee	539	0.00
adorn	559	0.00
enact	534	0.00
suspend	546	0.00
Low-frequency regular targets		
acrid	623	27.22
adverb	659	11.11
album	539	0.00
audit	558	5.56
bandit	534	0.00
blemish	542	5.56
blister	558	0.00
candid	572	0.00
canon	614	16.67
cathode	582	22.22
chowder	550	11.11
coffin	525	0.00
dwindle	575	0.00
eagle	521	0.00
falcon	551	0.00
fauna	576	0.00
gypsy	587	0.00
laundry	537	0.00
mammoth	545	0.00
mystic	559	0.00
nostril	539	0.00
orphan	539	0.00
privy	579	11.11
proxy	528	0.00
quibble	546	0.00
savvy	561	11.11
shudder	516	0.00
sibling	532	0.00
sigma	534	0.00
tepid	528	0.00
High-frequency irregular targets		
about	493	0.00
account	572	0.00
across	545	0.00
alone	493	0.00
along	513	0.00
amount	501	0.00
appear	554	0.00

Word	RT	%Error
attack	519	0.00
became	531	0.00
before	497	0.00
between	529	0.00
degree	533	0.00
despite	591	0.00
except	582	5.56
expect	529	5.56
extent	590	0.00
herself	527	0.00
himself	521	0.00
indeed	492	0.00
itself	573	0.00
perhaps	517	0.00
provide	532	0.00
report	512	0.00
respect	520	0.00
return	517	0.00
support	504	0.00
unless	566	0.00
until	526	0.00
hotel	545	0.00
around	491	0.00
High-frequency regular targets		
center	512	0.00
central	544	0.00
common	537	0.00
council	552	0.00
county	625	11.11
doctor	529	0.00
effort	495	0.00
fiscal	568	0.00
freedom	550	0.00
further	537	0.00
hundred	529	0.00
likely	522	0.00
little	530	0.00
meeting	500	0.00
member	526	0.00
method	510	0.00
morning	507	0.00
order	536	0.00
pattern	523	0.00
problem	503	0.00
public	532	0.00
second	506	0.00
simply	509	0.00
spirit	527	0.00
study	488	0.00
system	536	0.00
volume	554	0.00
western	552	0.00
written	537	0.00
normal	500	0.00

APPENDIX B

Algorithm Prediction and Human Stress Assignment for Nonwords in Experiment 2

Nonword	Algorithm prediction	Subjects initial (proportion)	Subjects final (proportion)
zortess	1	0.93	0.00
irsabe	1	0.47	0.40
ilgest	1	0.53	0.40
imwise	1	0.67	0.33
irsome	1	1.00	0.00
wodment	1	0.80	0.13
parness	1	0.73	0.27
loonise	1	0.47	0.53
mootite	1	0.73	0.27
loament	1	0.80	0.13
booness	1	0.73	0.27
horger	1	0.93	0.07
massest	1	0.47	0.53
gatted	1	1.00	0.00
yazzen	1	0.87	0.07
norring	1	1.00	0.00
furrage	1	0.80	0.20
daffish	1	0.93	0.07
bogdom	1	1.00	0.00
sagful	1	0.93	0.07
vighood	1	0.87	0.07
paddise	1	0.47	0.47
hobbite	1	0.93	0.07
vurtless	1	1.00	0.00
sartment	1	1.00	0.00
zirdness	1	1.00	0.00
chigor	1	0.93	0.07
wappous	1	0.73	0.2
birsome	1	0.93	0.07
nagward	1	1.00	0.00
zidy	1	1.00	0.00
famwise	1	0.93	0.07
hochic	1	1.00	0.00
tannid	1	1.00	0.00
vappish	1	1.00	0.00
beevast	1	0.87	0.13
vockine	1	0.60	0.33
sortise	1	0.87	0.13
zaffite	1	0.67	0.33
bafite	1	0.47	0.53
dirment	1	0.87	0.13
geavment	1	0.60	0.40
dastude	1	0.60	0.40
vabbage	1	0.93	0.07
zabage	1	0.8	0.07
pemment	1	0.73	0.27
vassive	1	0.93	0.07
tabive	1	0.53	0.47

Nonword	Algorithm prediction	Subjects initial (proportion)	Subjects final (proportion)
vebous	1	0.40	0.53
difboze	1	1.00	0.00
firtment	1	0.93	0.00
quimhet	1	0.73	0.27
tozkolt	1	0.87	0.00
beavnat	1	0.87	0.00
holpbon	1	0.93	0.00
rotgeap	1	0.80	0.07
seegmant	1	0.93	0.07
bitjeed	1	0.93	0.07
nurhact	1	0.60	0.33
zabnart	1	1.00	0.00
vabtaze	1	0.80	0.20
kortbeem	1	0.93	0.07
harbnaze	1	1.00	0.00
safnode	1	1.00	0.00
jovtirt	1	0.80	0.20
bimgant	1	0.87	0.07
gantmirt	1	1.00	0.00
pizlime	1	0.80	0.20
feagtin	1	1.00	0.00
kateway	1	1.00	0.00
peadote	1	1.00	0.00
goonoze	1	0.47	0.40
meerike	1	0.47	0.53
voobane	1	0.80	0.13
heanoke	1	0.73	0.20
doomipe	1	0.87	0.13
beakibe	1	0.87	0.07
veanope	1	0.80	0.13
fibeway	1	1.00	0.00
jaimipe	1	0.87	0.13
bomegoze	1	0.87	0.00
neethime	1	0.73	0.20
leabime	1	0.60	0.33
bittel	1	0.67	0.33
bennel	1	0.80	0.20
mestle	1	1.00	0.00
ekit	1	0.73	0.27
tuckle	1	1.00	0.00
pabble	1	1.00	0.00
dipple	1	1.00	0.00
portak	1	0.93	0.07
tilla	1	1.00	0.00
tosal	1	1.00	0.00
wortal	1	1.00	0.00
purdle	1	1.00	0.00
jortle	1	1.00	0.00
chakle	1	1.00	0.00
melpow	1	0.87	0.07
eadel	1	0.93	0.07
reasel	1	1.00	0.00
heakin	1	0.93	0.00

Nonword	Algorithm prediction	Subjects initial (proportion)	Subjects final (proportion)	Nonword	Algorithm prediction	Subjects initial (proportion)	Subjects final (proportion)
naipin	1	0.93	0.07	anness	2	0.07	0.93
peefin	1	0.93	0.07	berite	2	0.13	0.80
saizel	1	0.93	0.07	cokite	2	0.27	0.67
deavan	1	0.80	0.20	depite	2	0.13	0.87
laifun	1	1.00	0.00	dishood	2	0.47	0.53
kainip	1	0.73	0.20	enace	2	0.00	1.00
reakin	1	0.87	0.07	expite	2	0.20	0.80
leenad	1	0.93	0.07	inrant	2	0.60	0.40
domipe	1	0.53	0.47	misward	2	0.47	0.53
wirtife	1	0.80	0.20	reways	2	0.47	0.53
mirripe	1	0.40	0.60	unhood	2	0.47	0.53
birtoze	1	0.40	0.53	reless	2	0.07	0.80
emvoke	1	0.20	0.80*	akous	2	0.20	0.73
ilseeb	1	0.27	0.53*	monade	2	0.27	0.73
imream	1	0.20	0.80*	nokaire	2	0.07	0.93
gonnoze	1	0.13	0.80*	tovaise	2	0.20	0.80
merike	1	0.27	0.73*	yokate	2	0.53	0.47
hennoke	1	0.27	0.73*	rokee	2	0.53	0.47
jinnife	1	0.20	0.80*	baveen	2	0.07	0.87
dorrote	1	0.13	0.87*	fickeer	2	0.00	0.93
okone	1	0.13	0.87*	soctelle	2	0.20	0.80
nairoke	1	0.33	0.67*	tockenne	2	0.27	0.73
cavance	1	0.07	0.93*	hojese	2	0.40	0.60
kabist	1	0.33	0.67*	itesque	2	0.07	0.93
datance	1	0.33	0.67*	rizesse	2	0.07	0.87
emage	1	0.27	0.73*	wodette	2	0.13	0.87
voket	1	0.27	0.73*	riteur	2	0.13	0.80
ratine	1	0.27	0.73*	vodique	2	0.00	1.00
kifise	1	0.13	0.80*	dirhoo	2	0.47	0.47
satose	1	0.07	0.93*	bagoon	2	0.07	0.93
alave	2	0.00	1.00	galotte	2	0.00	1.00
aselt	2	0.00	1.00	nukteen	2	0.40	0.60
anofe	2	0.00	1.00	reakade	2	0.47	0.47
anift	2	0.00	1.00	seazaire	2	0.07	0.80
bepone	2	0.33	0.67	leenaise	2	0.20	0.73
covike	2	0.40	0.60	koonate	2	0.33	0.67
deseft	2	0.07	0.93	doaree	2	0.20	0.67
diskove	2	0.13	0.87	woareen	2	0.13	0.87
enift	2	0.00	1.00	doaneer	2	0.00	0.87
extope	2	0.20	0.80	maikelle	2	0.27	0.67
extip	2	0.20	0.80	raifenne	2	0.20	0.80
inirv	2	0.07	0.87	leamese	2	0.27	0.73
misbane	2	0.20	0.80	naikesque	2	0.13	0.87
misbon	2	0.60	0.40	leavette	2	0.20	0.80
retoke	2	0.27	0.73	joovine	2	0.40	0.53
retik	2	0.53	0.47	meenique	2	0.20	0.80
unvike	2	0.20	0.80	veefoo	2	0.60	0.40
commoke	2	0.00	1.00	beetoon	2	0.60	0.40
prenope	2	0.40	0.60	hoateen	2	0.47	0.47
prenip	2	0.47	0.53	noorate	2	0.53	0.40
rezoct	2	0.27	0.73	nockate	2	0.40	0.47
rezoke	2	0.13	0.87	corroze	2	0.07	0.93
avist	2	0.13	0.87	comirt	2	0.07	0.93

Nonword	Algorithm prediction	Subjects initial (proportion)	Subjects final (proportion)
comize	2	0.13	0.87
cadesce	2	0.00	0.93
coadesce	2	0.00	0.93

Note. Proportions do not sum to 1 in all cases because errors have been excluded. Items on which the algorithm performs particularly poorly are denoted by an asterisk.

APPENDIX C

Item Data: Experiment 3

Word	RT	%Error
Low-frequency irregular targets		
abbey	513	7.69
abject	571	42.31
abscess	600	15.38
accent	486	15.38
access	512	11.54
adjunct	533	69.23
advent	546	26.92
alley	506	11.54
allies	548	7.69
alloy	547	50.00
aloe	654	65.38
annals	601	42.31
annex	527	26.92
asses	517	61.54
asset	515	34.62
attic	524	0.00
augment	606	7.69
avid	557	26.92
banal	599	0.00
bombard	569	0.00
cadet	550	0.00
canal	562	7.69
caress	533	11.54
cement	511	0.00
compost	550	7.69
duress	564	0.00
endive	545	30.77
excerpt	583	38.46
exile	525	3.85
exit	492	0.00
grandeur	566	0.00
guitar	—	—
igloo	516	0.00
impulse	509	19.23
lament	515	7.69
latrine	607	11.54

Word	RT	%Error
oblong	545	11.54
outbid	549	0.00
outdid	555	0.00
pecan	540	0.00
perjure	569	30.77
quartet	535	0.00
rattan	580	38.46
romance	496	0.00
statute	539	7.69
subway	483	0.00
transcript	540	3.85
transit	528	3.85
tribute	530	0.00
voodoo	535	0.00
Low-frequency regular targets		
abhor	573	3.85
abduct	517	0.00
abstain	496	0.00
acquit	546	0.00
accuse	500	0.00
lawful	496	0.00
radish	491	0.00
eldest	500	0.00
allot	562	11.54
abort	499	0.00
annoy	462	0.00
annul	612	19.23
assort	530	0.00
assign	481	0.00
attain	482	0.00
atone	509	0.00
nasty	477	0.00
compute	521	0.00
lavish	492	0.00
endows	547	7.69
excites	565	0.00
kazoo	574	0.00
expel	518	0.00
impairs	497	0.00
obsess	543	3.85
sublet	519	11.54
aloof	512	0.00
ailment	550	0.00
album	517	0.00
otter	523	0.00
greedy	491	0.00
collect	501	0.00
umber	568	0.00
commute	501	0.00
flemish	519	0.00
grammar	507	0.00
loyal	501	0.00
figment	536	0.00
organ	503	0.00

Word	RT	%Error
taboo	515	0.00
tattoo	504	0.00
turban	511	0.00
proclaim	525	0.00
shipment	507	0.00
endless	503	0.00
pumping	495	0.00
manhood	515	0.00
abide	498	0.00
kingdom	499	0.00
punish	478	0.00
High-frequency irregular targets		
anode	—	—
college	505	0.00
commerce	521	15.38
common	478	0.00
effort	489	0.00
hotel	446	0.00
itself	468	0.00
marine	495	0.00
outside	479	0.00
person	444	0.00
High-frequency regular targets		
acting	502	0.00
matter	473	0.00
closer	477	0.00
market	489	0.00
alone	457	0.00
higher	458	0.00
along	478	0.00
payment	499	0.00
amount	463	0.00
complete	497	0.00

REFERENCES

Ans, B., Carbonnel, S., & Valdois, S. (1998). A connectionist multiple trace memory model for polysyllabic word reading. *Psychological Review,* **105,** 678–723.

Baayen, R. H., Piepenbrock, R., & van Rijn, H. (1993). *The CELEX lexical database (CD-ROM).* Linguistic Data Consortium, University of Pennsylvania, Philadelphia, PA.

Baker, R. G., & Smith, P. T. (1976). A psycholinguistic study of English stress assignment rules. *Language and Speech,* **19,** 9–27.

Baptista, B. O. (1984). English stress rules and native speakers. *Language and Speech,* **27,** 217–233.

Beckman, M. E. (1986). *Stress and non-stress accent.* Foris: Dordrecht.

Butterworth, B. (1992). Disorders of phonological encoding. *Cogntion,* **42,** 261–286.

Brown, P., Lupker, S. J., & Colombo, L. (1994). Interacting sources of information in word naming: A study of individual differences. *Journal of Experimental Psychology: Human Perception and Performance,* **20,** 537–554.

Chomsky, N., & Halle, M. (1968). *The sound pattern of English.* New York: Harper & Row.

Colombo, L. (1991). The role of lexical stress in word recognition and pronunciation. *Psychological Research,* **53,** 71–79.

Colombo, L. (1992). Lexical stress effect and its interaction with frequency in word pronunciation. *Journal of Experimental Psychology: Human Perception and Performance,* **18,** 987–1003.

Colombo, L., & Tabossi, P. (1992). Strategies and stress assignment: Evidence from a shallow orthography. In R. Frost & L. Katz (Eds.), *Orthography, phonology, morphology, and meaning* (pp. 319–340). Amsterdam: Elsevier.

Coltheart, M. (1978). Lexical access in simple reading tasks. In G. Underwood (Ed.), *Strategies of information processing* (pp. 151–216). London: Academic Press.

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

Coltheart, M. (1996). Computational modeling and cognitive psychology. *Noetica,* Issue 1. http://psych.psy.uq.oz.au/CogPsych/Noetica/OpenForum.

Coltheart, M., Curtis, B., Atkins, P., & Haller, M. (1993). Models of reading aloud: Dual-route and parallel-distributed-processing approaches. *Psychological Review,* **100,** 589–608.

Coltheart, M., & Rastle, K. (1994). Serial processing in reading aloud: Evidence for dual-route models of reading. *Journal of Experimental Psychology: Human Perception and Performance,* **20,** 1197–1211.

Coltheart, M., Rastle, K., Perry, C., Langdon, R., & Ziegler, J. (in press). DRC: A dual-route cascaded model of visual word recognition and reading aloud. *Psychological Review.*

Forster, K. I., & Chambers, S. M. (1973). Lexical access and naming time. *Journal of Verbal Learning and Verbal Behavior,* **12,** 627–635.

Forster, K. I., & Forster, J. C. (1990). User's guide to the DMASTR display system: Laboratory software for mental chronometry. [unpublished document]

Fudge, E. C. (1984). *English word stress.* London: Allen & Unwin.

Garde, P. (1968). *L'Accent.* Paris: Presses Univ. France.

Humphreys, G. W., & Evett, L. J. (1985). Are there independent lexical and nonlexical routes in word processing? An evaluation of the dual-route theory of reading. *Behavioral and Brain Sciences,* **8,** 689–740.

Jared, D. (1997). Spelling-sound consistency affects the naming of high-frequency words. *Journal of Memory and Language,* **36,** 505–529.

Kelly, M. H., & Bock, J. K. (1988). Stress in time. *Journal of Experimental Psychology: Human Perception and Performance,* **14,** 389–403.

Kelly, M. H., Morris, J., & Verrekia, L. (1998). Orthographic cues to lexical stress: Effects on naming and lexical decision. *Memory & Cognition,* **26,** 822–832.

Kingdon, R. (1958). *The groundwork of English stress.* London: Longman.

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

Laudanna, A., Burani, C., & Cermele, A. (1994). Prefixes as processing units. *Language and Cognitive Processes,* **9,** 295–316.

Levelt, W. J. M. (1992). Accessing words in speech production: Stages, processes and representations. *Cognition,* **42,** 1–22.

Levelt, W. J. M., & Wheeldon, L. (1994). Do speakers have access to a mental syllabary? *Cognition,* **50,** 239–269.

Liberman, M., & Prince, A. S. (1977). On stress and linguistic rhythm. *Linguistic Inquiry,* **8,** 249–336.

Marslen-Wilson, W., Tyler, L. K., Waksler, R., & Older, L. (1994). Morphology and meaning in the English mental lexicon. *Psychological Review,* **101,** 3–33.

Monsell, S., Doyle, M. C., & Haggard, P. N. (1989). Effects of frequency on visual word recognition tasks: Where are they? *Journal of Experimental Psychology: General,* **118,** 43–71.

Paap, K. R., & Noel, R. W. (1991). Dual-route models of print to sound: Still a good horse race. *Psychological Research,* **53,** 13–24.

Patterson, K. E., & Morton, J. (1985). From orthography to phonology: An attempt at an old interpretation. In K. Patterson, J. C. Marshall, & M. Coltheart (Eds.), *Surface dyslexia* (pp. 335–359). London: Erlbaum.

Patterson, K. E., & Shewell, C. (1987). Speak and spell: Dissociations and word-class effects. In M. Coltheart, G. Sartori, & R. Job (Eds.), *The cognitive neuropsychology of language* (pp. 273–294). London: Erlbaum.

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

Rastle, K., & Coltheart, M. (1998). Whammies and double whammies: The effect of length on nonword reading. *Psychonomic Bulletin and Review,* **5,** 277–282.

Rastle, K., & Coltheart, M. (1999a). Serial and strategic processing in reading aloud. *Journal of Experimental Psychology: Human Perception and Performance,* **25,** 482–503.

Rastle, K., & Coltheart, M. (1999b). Lexical and nonlexical phonological priming in reading aloud. *Journal of Experimental Psychology: Human Perception and Performance,* **25,** 461–481.

Seidenberg, M. S., & McClelland, J. L. (1989). A distributed, developmental model of word recognition and naming. *Psychological Review,* **96,** 523–568.

Seidenberg, M. S., Waters, G. S., Barnes, M. A., & Tanenhaus, M. K. (1984). When does irregular spelling or pronunciation influence word recognition? *Journal of Verbal Learning and Verbal Behavior,* **23,** 383–404.

Smith, P. T., & Baker, R. G. (1976). The influence of English spelling patterns on pronunciation. *Journal of Verbal Learning and Verbal Behavior,* **15,** 267–285.

Taft, M., & Forster, K. (1975). Lexical storage and retrieval of prefixed words. *Journal of Verbal Learning and Verbal Behavior,* **14,** 637–647.

Trammell, R. (1978). The psychological reality of underlying forms and rules for stress. *Journal of Psycholinguistic Research,* **7,** 79–94.

Williams, B. (1987). Word stress assignment in a text-to-speech synthesis system for British English. *Computer Speech and Language,* **2,** 235–272.

Zorzi, M., Houghton, G., & Butterworth, B. (1998). Two routes or one in reading aloud? A connectionist dual-process model. *Journal of Experimental Psychology: Human Perception and Performance,* **24,** 1131–1161.

(Received November 3, 1998)
(Revision received August 18, 1999)