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Word Frequency, Repetition, and Lexicality Effects in Word Recognition Tasks: Beyond Measures of Central Tendency

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Response time (RT) distributions obtained from 3 word recognition experiments were analyzed by fitting an ex-Gaussian function to the empirical data to determine the main effects and interactive influences of word frequency, repetition, and lexicality on the nature of the underlying distributions. The ex-Gaussian analysis allows one to determine if a manipulation simply shifts the response time (RT) distribution, produces a skewing of the RT distribution, or both. In contrast to naming performance, the lexical decision results indicated that the main effects and interactions of word frequency, repetition, and lexicality primarily reflect increased skewing of the RT distributions, as opposed to simple shifts of the RT distributions. The implications of the results were interpreted within a hybrid 2-stage model of lexical decision performance.

One of the most robust, and probably least surprising, empirical observations in the word recognition literature is that the frequency of exposure to a word modulates the ease with which that word is processed in the future. This phenomenon is reflected in both the word-frequency effect in which extant word-frequency counts (e.g., Kucera & Francis, 1967, norms) predict lexical decision and naming performance (e.g., Balota & Chumbley, 1984, 1985; Monsell, Doyle, & Haggard, 1989) and repetition effects in which the experimental exposure to a word facilitates subsequent lexical decisions and word naming performance to that word (e.g., Duchek & Neely, 1989; Forster & Davis, 1984; Scarborough, Cortese, & Scarborough, 1977). The present research provides a further exploration of the influence of these variables, with the main departure being an attempt to increase the level of sophistication concerning the analysis of the primary dependent measure used in past chronometric studies of these variables (i.e., RT). In particular, instead of estimating a mean (or median) RT for a given level of frequency or repetition, we provide estimates of parameters that characterize the shape of the RT distribution.[1] We demonstrate that such analyses provide important insights into theoretical accounts of word-frequency and repetition effects in word recognition tasks, and, like others (e.g., Balota, Spieler, & Faust, 1994; Heathcote, Popiel, & Mewhort, 1991; Hockley, 1984; Hohle, 1965; Logan, 1992; Mewhort, Braun, & Heathcote, 1992; Ratcliff, 1978, 1979; Spieler, Balota, & Faust, 1996; Wixted & Rohrer, 1993), argue that it is important for researchers to begin understanding how variables influence the nature of RT distributions above and beyond estimates of central tendency. We have selected repetition and frequency effects in word recognition as our target factors for these analyses because these are two of the most replicated effects in the literature, and have received a considerable amount of theoretical and empirical attention. However, before turning to the theoretical and empirical controversies regarding word-frequency and repetition effects, we first provide a brief overview of the motivation for characterizing RT distributions instead of using estimates of central tendency such as the means or medians of conditions.

RT Distributions and Chronometric Analyses

In most chronometric studies of information processing, researchers obtain a set of observations within a given condition for each participant. A mean or median is calculated which provides an estimate of the central tendency for that condition. These estimates of the central tendencies are then submitted to inferential tests (e.g., analyses of variance). If there is a consistent difference between the means of conditions across participants, the inferential test yields a reliable effect, and hence the researcher concludes that the manipulation had an effect.

Consider the implicit assumptions concerning the nature of the RT distributions between two conditions that are *reliably* different. First, recall that RT distributions are positively skewed. At the simplest level, when one obtains a

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[1] It is noteworthy that we are not using the word *shape* in the statistical sense here. We are simply referring to the fact that distributions change in some way above and beyond simple shifts of the distribution along some time axis.

reliable difference between two means one might assume that the shapes of the two distributions are identical, with the exception of a simple shift along the RT scale. Such a situation is displayed by comparing the distributions in Figure 1A with Figure 1B. We would argue that this is the most prevalent inference drawn from the observation of a reliable difference between two conditions in chronometric studies. Of course, there are a number of alternative ways in which one may obtain a reliable difference. For example, by comparing Figure 1A with Figure 1C, one can see that there is relatively little shift in the modal portion of the distribution, but there is a small percentage of observations in the tail of the distribution that increases the overall mean of the distribution. In addition, as shown by comparing Figures 1A and 1D, it is possible that a manipulation has opposing influences on the modal portion of the distribution and the tail of the distribution. Here, on the basis of analyses of means, the researcher would be erroneously led to argue that there is no effect of the manipulation and yet the manipulation has opposing influences on different characteristics of the RT distribution.

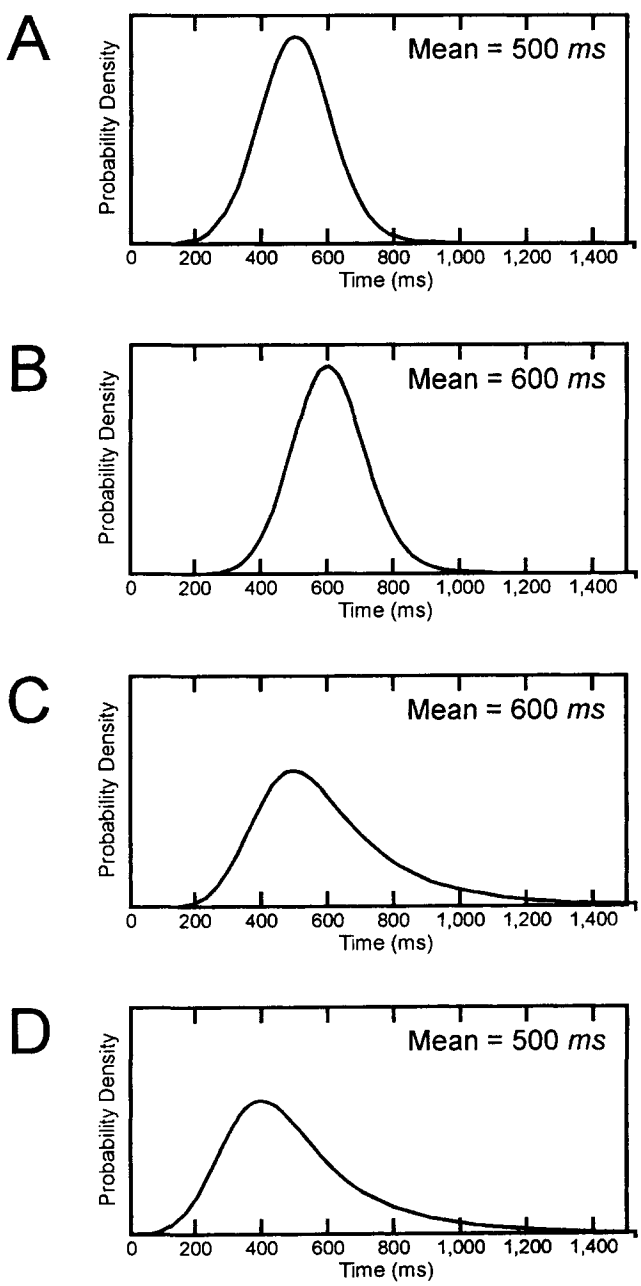

Figure 1. Examples of reaction time distributions that trade off modal portions of the distributions and the degree of skewness of the distributions.

The above interpretative ambiguity occurs whenever one uses estimates of central tendency to describe the characteristics of the underlying RT distributions. As shown in Figure 1, there is considerably more information available in the distribution than simply the estimate of central tendency. Unfortunately, there are a number of well-documented problems in estimating the commonly known higher moments of RT distributions that presumably capture the shape of the distribution, such as skewness and kurtosis. For example, a number of researchers have demonstrated that higher order moments of RT distributions are extremely sensitive to outliers (see, for example, Ratcliff, 1979). Thus, although most chronometric researchers are well-aware of the problems associated with estimates of central tendency displayed in Figure 1, estimates of higher-order moments do not provide a useful alternative in capturing the change in shape of underlying reaction distributions due to an influence of an independent variable.

Fortunately, however, there does appear to be a way of providing estimates of the shape of RT distributions. The approach involves assuming an explicit mathematical function and fitting the empirical data to that function to obtain parameter estimates of the underlying theoretical distribution. The present study uses this approach by fitting empirical reaction time distributions to the ex-Gaussian distribution. Although a number of researchers have shown that the convolution of a Gaussian and an exponential distribution (i.e., the ex-Gaussian distribution) yields a relatively good fit to empirical RT distributions (Heathcote et al., 1991; Hockley, 1984; Hohle, 1965; Luce, 1986; Mewhort et al., 1992; Spieler et al., 1996; Wixted & Rohrer, 1993), it was Ratcliff's (1978, 1979) pioneering work which most fully demonstrated the stability of the estimates, along with the utility of this approach in testing an explicit model of memory retrieval. In fitting an empirically obtained RT distribution to the ex-Gaussian distribution, one obtains estimates of three parameters: Mu, which reflects the mean of the Gaussian component of the distribution, Sigma, which reflects the standard deviation associated with the Gaussian component, and Tau, which reflects the mean and standard deviation associated with the exponential component of the distribution.

Figure 2 displays how Gaussian and exponential distributions can be combined to produce the typically observed skewed distribution. Figure 2A displays a Gaussian distribution (Mu = 500 and Sigma = 100) with no exponential component (Tau = 0). Figure 2B displays an exponential

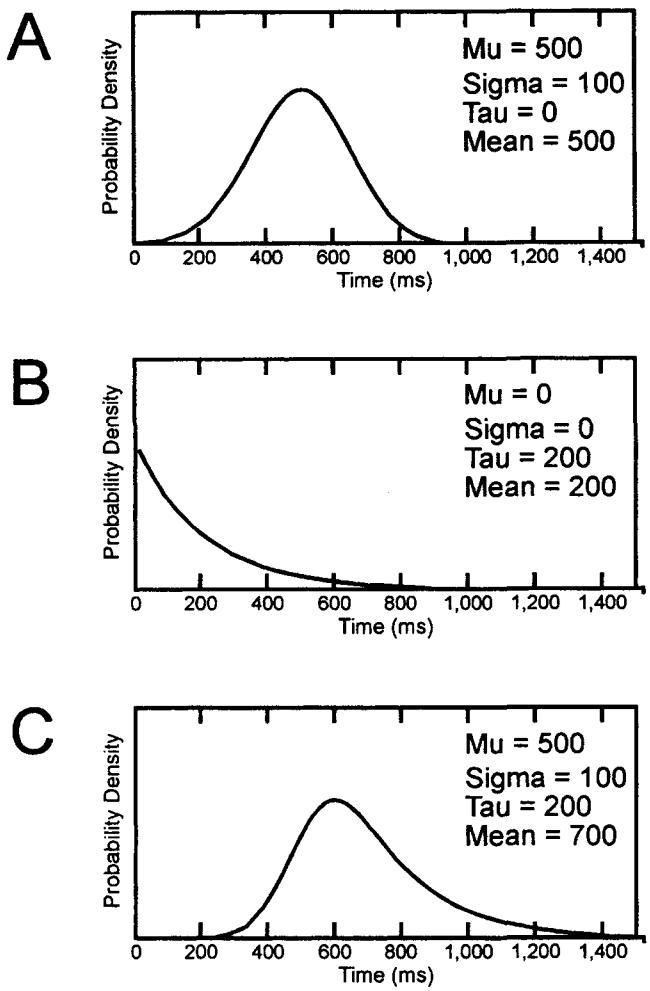

Figure 2. Gaussian (A), exponential (B), and ex-Gaussian (C) distributions along with the parameter estimates from an ex-Gaussian analysis. Note that the distribution in Figure 2C is the convolution of the distributions in Figures 1A and 1B. For illustrative purposes, the probability density function is rescaled across panels.

distribution (Tau = 200) with no Gaussian component (Mu = 0 and Sigma = 0). Figure 2C displays the typically observed skewed distribution, which, as shown in Figure 2, is simply a convolution of the distributions in Figures 2A and 2B. Although only an approximation, a useful metaphor in helping to understand the ex-Gaussian approach is to simply fold the left leading edge of the fitted curve across the middle of the Gaussian component. The remaining portion of the distribution is the exponential component, Tau, which is related to an estimate of skewness. A particularly powerful aspect of the ex-Gaussian function is that the mean of the distribution is the sum of Mu and Tau (see the mean values across Figures 1A, 1B, and 1C). Thus, returning to our original example, if one finds a difference in the means of two conditions, one can determine if this is due to (a) a change in the Gaussian component (Mu), (b) a change in the exponential component (Tau), or (c) a change in both. Moreover, as suggested in Figure 1D, it is possible to find a trade-off in Mu and Tau, such that both are changing but in opposite directions. This pattern can produce a null effect of condition based on analyses on means. In fact, this is precisely the pattern that has been reported in two studies measuring the facilitatory effects found in Stroop color naming (see Heathcote et al., 1991; Spieler et al., 1996). Specifically, the congruent condition produced a decrease in Mu compared to the neutral condition, but an increase in Tau. Obviously, finding a trade-off in parameters has quite different theoretical implications than finding no effect of the manipulation on the basis of estimates of central tendency.

Of course, the goal of chronometric analyses is to provide insight into the cognitive processes that produce an observed difference. What insights can one gain from estimates of Mu, Sigma, and Tau, above and beyond simple estimates of central tendency? We believe that such analyses are particularly important for two reasons: First, with the advent of the increased level of sophistication in computational models, one can now make predictions concerning how a variable changes the shape of the underlying RT distribution instead of simply making the prediction that a variable may or may not produce an effect, as reflected by changes in central tendency. For example, Mewhort et al. (1992) recently used the ex-Gaussian analysis to test the predictions from a connectionist model of Stroop performance developed by Cohen, Dunbar, and McClelland (1990). In addition, Wixted and Rohrer (1993) used an ex-Gaussian analysis of the distribution of recall latencies to discriminate specific models of proactive interference. In both studies, the detailed predictions of the specific models could not have been tested with estimates of central tendency (also see Ratcliff, 1978; Ratcliff & Murdock, 1976).

A second, more speculative aspect of the ex-Gaussian analysis is that it is possible that different characteristics of the RT distribution may reflect different types of cognitive processes. For example, one of the most widely used distinctions in cognitive research is between more stimulus driven, automatic (nonanalytic) processes and more central, attentional (analytic) processes (e.g., Balota, 1983; Hasher & Zacks, 1979; Jacoby, 1991; Neely, 1977; Posner & Snyder, 1975; Schneider & Shiffrin, 1977). Although there clearly are alternative interpretations, which are presented in the *General Discussion* section, it is possible that the Gaussian component of the RT distribution can, in some cases, provide a marker for the more stimulus driven automatic (nonanalytic) processes, whereas the exponential component of the RT distribution provides, in some cases, a marker for the more central attention demanding (analytic) processes. For example, Hohle (1965) suggested that performance in a given task likely includes a number of early perceptual operations and a number of later response operations. Assuming that each of these operations is due to relatively short-lived components of performance, each with their own underlying distributions and similar variances, one might appeal to the central limit theorem to argue that the sum of these distributions may combine to produce a normal distribution, as reflected in the Gaussian component. However, it is possible that on some trials, the output from these

more automatic processes (reflected in the Gaussian component of the RT distribution) is not sufficient to drive a response. It is on these trials that the participant may engage a slower more analytic and attention demanding process. In fact, one of the hallmarks of attentional processes is that they are relatively slower to engage than more automatic processes (see, for example, Balota, Black, & Cheney, 1992; Neely, 1977; Posner & Snyder, 1975). If this is the case, then the response latencies on those trials in which this additional attention demanding process is engaged would be distinct from the response latencies that reflect the Gaussian component and may be reflected in a skewing of the RT distribution, which is captured in the exponential component of the ex-Gaussian (i.e., Tau).

Although the above mapping of processes onto cognitive components has some intuitive appeal, there is considerable controversy and debate regarding this mapping (see Luce, 1986, for some discussion). Ultimately, it is likely that the interpretation of the different components of the RT distribution will depend upon the explicit conceptualization of a theoretical framework to account for performance within a given task. It is in this light that we have selected word-frequency and repetition effects as the targets for analyses in the present series of experiments. We shall now turn to a discussion of how the ex-Gaussian analyses may provide insights into the nature of both word-frequency and repetition effects in word recognition tasks.

Word-Frequency and Repetition Effects

Although word-frequency and repetition effects are among the most robust findings in the word recognition literature, as noted above, there has been considerable empirical and theoretical discussion of the nature of these effects. For example, there are a number of quite distinct classes of models that have been proposed to account for word-frequency and repetition effects in word recognition tasks. One of the classic accounts is Morton's (1969) logogen model. According to this model, each word recognition device, referred to as a logogen, has associated with it a frequency sensitive threshold. When featural analyzers provide sufficient activation for a given logogen to surpass its corresponding threshold, the word is recognized, that is, the participant presses the "word" button in a lexical decision task or begins implementing output of the word in a naming task. A different account of word-frequency effects was proposed by Forster (1976). In this model, frequency effects are produced by means of a frequency-ordered search of an orthographically defined subset of the lexicon. Becker (1980) has developed a hybrid model that includes both logogen-type devices along with frequency-ordered search sets. These first wave models have been primarily used to accommodate the extant literature concerning estimates of central tendency, and we are unaware of any explicit attempt to extend these models to characteristics of RT distributions. However, as noted above, there are more recent parallel distributed processing models of word naming (e.g., Seidenberg & McClelland, 1989; Plaut, McClelland, Seidenberg, & Patterson, 1996), and lexical decisions (e.g., Seidenberg & McClelland, 1989) that do make predictions concerning the underlying RT distributions.[2] In these models, word-frequency effects are implemented by means of the weights that connect input units to hidden units and hidden units to output units by means of a frequency-sensitive training regime. Although these second wave models do in fact make specific predictions at the level of RT distributions, these models have typically been examined at the level of estimates of central tendency (see, however, Balota & Spieler, 1998; Besner & Bourassa, 1995; Spieler & Balota, 1997).

In addition to the diversity of models that have attempted to accommodate the influence of word frequency on word recognition tasks, there has also been controversy regarding the influence of task-specific operations in the tasks used to study lexical processing (see Balota & Chumbley, 1984, 1985, 1990; Besner & Swan, 1982; Connine, Mullennix, Shernoff, & Yelens, 1990; Monsell et al., 1989; Savage, Bradley, & Forster, 1990). Specifically, there has been a concern that some portion of the observed word-frequency effect in specific tasks may not necessarily reflect the general architectural characteristics of the word processing system, but may include operations idiosyncratic to tasks used to measure word recognition performance (i.e., naming and lexical decision tasks). Consider for example, the familiarity-based models of lexical decision performance developed by Balota and Chumbley (1984), Besner (1983), and Besner and Swan (1982). These models place a relatively large emphasis on the types of information that are available to participants to make word–nonword discriminations. Because words are more familiar than nonwords (also more meaningful), familiarity would be a useful piece of information to discriminate between the two classes of stimuli in the lexical decision task. When viewed in this way, low-frequency words may produce longer lexical decision times because these items are more similar to the nonwords on the relevant familiarity dimension.

The present study explores a particular instantiation of a familiarity-based model displayed in Figure 3. According to this model, if a stimulus is high on the familiarity–meaningfulness (FM) dimension (above the upper criterion), participants can make a fast "yes" response, whereas, if the stimulus is low on the familiarity–meaningfulness dimension (below the low criterion), participants can make a fast "no" response. If the stimulus is between the upper and lower criterion the participant is likely to engage in a more time consuming attention-demanding analytic process which increases response latencies. For example, the participant may be forced to check the spelling of the stimulus, or retrieve its semantic referent. In either case, because low-frequency words are lower on the FM dimension than

[2] In addition to the connectionist models, there are alternative computational models developed (e.g., Coltheart, Curtis, Atkins, & Haller, 1993; Grainger & Jacobs, 1996) that have the potential to make predictions regarding the ex-Gaussian distribution. Because of the emphasis on lexical decision performance in the Grainger and Jacobs (1996) model, this model appears ideally suited for analyses similar to those performed in this study.

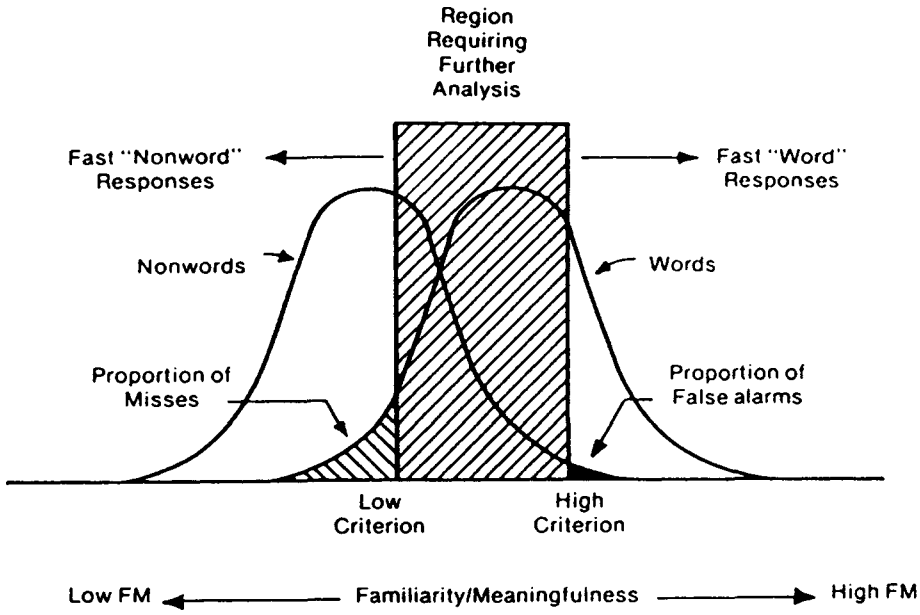

Figure 3. A two-stage model of the lexical decision task. FM = familiarity/meaningfulness. From "Are Lexical Decisions a Good Measure of Lexical Access? The Role of Word Frequency in the Neglected Decision Stage," by D. A. Balota and J. I. Chumbley, 1984, *Journal of Experimental Psychology: Human Perception and Performance, 10,* p. 352. Copyright 1984 by the American Psychological Association.

high-frequency words, these items are more likely to engage the slower analytic search process. The important point here is that the frequency effect in the lexical decision task may be exaggerated because of an additional task specific search process that is engaged when participants are required to discriminate familiar words from unfamiliar nonwords.

Let us consider the predictions from the two-stage model concerning the manner in which RT distributions should be modulated by word frequency in the lexical decision task. The most straightforward prediction is that the RT distribution of the low-frequency words will have a larger Tau component than the distribution of the high-frequency words, because an increased number of these items will undergo a more analytic attention demanding process.[3] Interestingly, there is some recent evidence that suggests this prediction is correct (Plourde & Besner, 1997). Although the mere increase in the Tau component for low-frequency words, compared to high-frequency words, is not a strong discriminator amongst word recognition models, as described below, the two-stage model does make additional predictions regarding the locus of both the Word Frequency × Repetition and the Lexicality × Repetition interactions. The present series of experiments explore each of these predictions in the lexical decision task (Experiment 1), and also in a task that does not include the same emphasis on the binary discrimination between familiar words and unfamiliar nonwords (i.e., speeded word naming [Experiments 2 and 3]).

Experiment 1

The goal of the first experiment is to examine the influence of word frequency, repetition, and lexicality on the shape of the RT distributions, as reflected by an ex-Gaussian analysis. In pursuit of this goal, we provide an analysis of the RT distribution results from a study by Balota and Ferraro (1996). The design of this study is displayed in Table 1. As shown here, participants engaged in two different phases. During the first phase, participants made rhyme judgments to both high- and low-frequency words along with a set of nonwords. Across participants, each stimulus was paired with a rhyming pair mate and a nonrhyming pair mate. During the second phase, see bottom of Table 1, participants made lexical decisions to both the stimuli that were presented earlier along with an equal set of new stimuli. It is noteworthy that because participants made rhyme decisions during the first phase and lexical decisions during the second phase, this design allows one to factor out the influence of stimulus repetition on the decision and response components of the task.

Now, let us consider the most straightforward predictions from the two-stage model for the lexical decision perfor-

[3] It is also possible that depending upon the probabilities of the two processes that one might predict a bimodal response latency distribution. However, given the empirical observation that the ex-Gaussian distribution fits response latency distributions quite well, the more likely candidate is that a change in τ will occur. These issues are more fully explored in the modeling section.

Table 1
Examples of Stimuli Presented in Phase 1 (Rhyme Phase) and Phase 2 (Lexical Decision Phase)

Phase/task	HF word	LF word	Nonword
Rhyme judgments			
Rhyming pairs	where–air	four–chore	tube–doob
Nonrhyming pairs	gritty–carry	slide–rude	strong–hing
Lexical decision			
Repeated			
Rhyme "yes"	air	chore	doob
Rhyme "no"	carry	rude	hing
Nonrepeated	feet	jilt	neek
	pretty	gravel	dimp

Note. HF = high frequency; LF = low frequency.

mance. First, consider the word-frequency effect. As noted above, according to the two-stage model, this effect should primarily modulate the Tau component, because low-frequency words are more likely to incur the second more attention demanding stage. Second, consider the Word Frequency × Repetition interaction, that is, the larger facilitatory influence of repetition for low-frequency words than for high-frequency words. According to the two-stage model, this interaction should primarily be in the Tau component, because the repetition of low-frequency items are more likely to push these words above the upper criterion, thereby decreasing the need for the additional attentional stage, at least compared to the repetition of high-frequency words. Finally, consider the Repetition × Lexicality interaction. If one separates out the influence of repetition of response and decision (as in the present design), the two-stage model predicts a facilitatory benefit of repetition for words, but an *inhibitory* effect of repetition for nonwords. The latter prediction is due to the fact that repetition should boost the familiarity of some of the nonwords above the lower threshold, thereby increasing the likelihood of such items engaging the more attention demanding analytic search process. Moreover, because the analytic search process is slower than the familiarity-based process, one should primarily find effects of this factor in the Tau component.

In sum, the first experiment provides an analysis of the influence of lexicality, repetition, and word frequency on the shape of the RT distributions obtained from a lexical decision task. The predictions concerning the influence of variables are based on the two-stage model of lexical decision performance. The second experiment explores these same variables in a task that does not include the explicit binary discrimination between familiar word and unfamiliar nonwords (i.e., speeded naming performance). Although we believe that the results of the present analyses have implications for models of word recognition and the tasks that are used to build word recognition models, we also believe that these analyses make a more general point regarding the importance of analyses beyond single point estimates of central tendency. As we shall see, there is considerably more to the influence of word frequency, lexicality, and repetition than changes in estimates of central tendency. Moreover, we shall also demonstrate that the present results provide considerable constraints on the extant models, and in fact an unembellished two-stage model has considerable difficulty accounting for some of the RT distribution changes.

Method

Participants. Forty-eight individuals recruited from undergraduate courses at Washington University participated in this experiment. The mean age for these individuals was 20.1 years.

Apparatus. Stimulus presentation and data collection were controlled by an Apple IIe microcomputer (Apple Computer, Inc., Cupertino, CA) that was interfaced with a clock card that provided an estimate of response latencies to the nearest millisecond.

Materials. Three hundred and twenty high-frequency words (more than 100 counts per million) and 320 low-frequency words (less than 5 occurrences per million) were selected from the Kucera and Francis (1967) norms. Within each frequency range 160 words were selected as word stimuli and 160 words were selected to construct nonwords by changing one or two letters to produce pronounceable nonwords. The words and nonwords within each frequency range were matched on length in letters and syllables. Across frequency ranges, the stimuli were matched in length in letters and syllables. For each target stimulus, a rhyming pair mate and a nonrhyming pair mate word was selected for the Phase 1 rhyming task. The rhyming and nonrhyming pair mates were selected such that participants could not use overlap in orthography as a cue to make the rhyme decision (e.g., *cause-laws* for a rhyming pair and *cause-raise* for a nonrhyming pair). Rhyming and nonrhyming pair mates were selected for the nonwords in the similar fashion (e.g., *spart-cart* for a rhyming pair and *shart-hurt*, for a nonrhyming pair). In addition to the stimuli that served as targets, an additional 56 stimuli (28 words and 28 nonwords) served as practice-buffer stimuli. Each of these stimuli also had a rhyming and nonrhyming pair mate.

During the rhyming task, stimuli were counterbalanced across participants such that no target word, nonword, or pair mate was repeated for a given participant, and each word and nonword occurred equally in both the rhyme and nonrhyming conditions. There were 20 observations in each of the cells that were produced by crossing word frequency, lexicality, and rhyme decision (i.e., a total of 160 items; because word frequency for nonwords is zero, this was a pseudo-variable that was included for counterbalancing purposes). During the lexical decision phase, participants were presented with the 160 items that earlier occurred in the rhyme task, along with an additional 160 items that varied along the same stimulus dimensions. Items were again counterbalanced across lists such that no stimulus appeared more than once for a given participant, and each stimulus was rotated across the factors, repetition, and rhyme response across participants. Because "response" during the rhyme task (i.e., "yes" vs. "no") did not modulate later lexical decision performance (see Balota & Ferraro, 1996, for details), we collapsed across this dimension, so that each cell of the lexical decision task included 40 observations.

Procedure. Participants were tested alone in a sound deadened room. During the rhyming phase of the experiment, the following series of events occurred: (a) a row of three asterisks (* * *) was presented in the center of the screen for 330 ms; (b) a rhyming or nonrhyming word replaced the fixation pattern and was presented for 1,250 ms in the center of the screen; (c) after a blank screen of 17 ms, the target word or nonword was presented immediately after the rhyming stimulus in the same location; (d) the participant pressed either the / (slash) key or the *z* key on the keyboard to

indicate "yes" the pair rhymed or "no" the pair did not rhyme, respectively; and (e) if a correct response was made, then this cleared the screen and initiated the 2,500-ms intertrial interval; if an incorrect response was made an error message ("YOU PRESSED THE WRONG KEY") was presented on the screen and then a keypress both cleared the screen and began the 2,500-ms intertrial interval. There were 24 practice trials presented during the rhyme task, which were followed by two test blocks of 80 trials each. Conditions were equally represented within each test block, and each block was preceded by four buffer trials.

After the rhyme phase, participants received a 5-min rest period. Participants were then given instructions for the lexical decision phase of the experiment. On each trial the following sequence of events occurred: (a) a row of three asterisks (* * *) was presented in the center of the screen for 330 ms; (b) a word or nonword stimulus replaced the asterisks; (c) the participant pressed either the / key or the z key to indicate word or nonword, respectively; and (d) a correct response cleared the screen and initiated the 2,500-ms intertrial interval; if an incorrect response was made, the message "ERROR" was presented, which was terminated by a keypress by the participant that cleared the screen and began the 2,500-ms intertrial interval. Participants first received 24 practice trials that were followed by two test blocks of 160 trials each. Conditions were equally represented within each test block, and each test block was preceded by four buffer trials.

During both phases, participants were seated approximately 60 cm from the computer screen. They were encouraged to respond as fast and as accurate as possible. There was a mandatory break at the end of the practice blocks and between the test blocks within each phase. Stimuli within both the practice block and test block were randomly ordered anew for each participant. The experiment lasted approximately 1 hr.

Results

The first analyses presented are on the Phase 2 lexical decision data. Because the Phase 1 rhyme data are identical across Experiments 1 and 2, we have delayed reporting these data until after Experiment 2 to avoid any redundancy.

In order to insure that the current analyses were not unduly influenced by extreme response latencies, we used the following screening procedures. First, an overall mean and standard deviation was calculated for each participant's lexical decision performance. Any observation that was greater than 2.5 *SD*s above the mean or greater than 3,000 ms, and any response that was less than 2.5 *SD*s below the mean or less than 250 ms was treated as an outlier, and removed. The mean percentage of outliers for the lexical decision task was 3%. Because the present analyses primarily emphasize the characteristics of the RT distributions, we focus on the RT data instead of error rates. However, there was no evidence of speed-accuracy trade-offs in the present data, and the interested reader is directed to Balota and Ferraro (1996) for full details.

Fitting the ex-Gaussian. Ratcliff (1979) has argued that one needs approximately 100 observations per condition to fit the ex-Gaussian distribution, which, although relatively large, is an order of magnitude smaller than one needs to obtain stable estimates of skewness. The smallest cells in the present design contained 40 observations per participant cell. Fortunately, when the number of observations per participant cell falls below the needed 100, one can use Vincent averaging, or Vincentizing, to combine distributions from multiple participants in a manner that does not distort the shape of the distributions (Ratcliff, 1979; Vincent, 1912). This procedure involves rank ordering each participant's RTs within a cell. The data are then divided into a set of 20 quantiles, and the mean of each quantile per participant is calculated. Corresponding quantiles are then averaged across 4 participants in the present case to produce super-subjects on which the ex-Gaussian distribution is fit. The fits of the super-subjects to the ex-Gaussian were accomplished by means of the RTSYS statistical package developed by Heathcote (1993). The fits of the theoretical curve to the empirical data were then evaluated using a chi-square goodness of fit test. None of the fits was rejected at the .05 level, thereby suggesting that the ex-Gaussian did reasonably well at capturing the empirical distributions. [4]

Figure 4 displays the fit of the ex-Gaussian function across participants to the empirical data. (The actual parameter estimates are presented next.) As shown here, the function was fit to 20 quantiles, each reflecting 5% of the participants' data. The six panels refer to the critical comparisons of frequency, repetition, and lexicality. Consistent with the chi-square goodness-of-fit-test, as shown here, the functions fit the data relatively well. We shall now turn to direct tests of the parameter estimates.

The present analyses were motivated by a set of distinct hypotheses concerning the influence of repetition, lexicality, and word frequency. Each of these hypotheses are discussed in turn. Within each section, a set of within-participants analyses of variance (ANOVAs) are presented on the traditional mean RT data, along with ANOVAs on the components of the ex-Gaussian analyses that were fitted to the super-subjects. Unless otherwise indicated, all significant effects have p values less than the .05 level.

Word-frequency effects. One of the primary issues motivating the present analyses is the influence of word frequency on the characteristics of the RT distributions. As shown in Table 2, the influence of word frequency does not simply shift the distribution, as would be reflected by a shift in Mu, but also there appears to be a considerable increase in the tail of the distribution, as reflected by an increase in the Tau component. In particular, there is a word-frequency effect of 63 ms in the means, with approximately 29 ms due to a shift in the Gaussian component and 35 ms due to an increase in the exponential component for low-frequency words, compared to high-frequency words. Thus, over half of the word-frequency effect appears to be in the stretching

[4] The chi-square test is only being used here as an approximation to test the quality of fits of the present distributions. Clearly, it would be inappropriate to simply rely on this measure without visually inspecting the fits, because as in other measures the ability to reject the null hypothesis is dependent upon the power of the test. The present individual distributions were fit quite well based on visual inspection. Also, as shown in Figures 3 and 4, the overall distributions per condition are fit by the ex-Gaussian functions. Of course, this is not surprising in light of the arguments by Luce (1986) and Ratcliff (1979) regarding the utility of the ex-Gaussian distribution to fit RT distributions.

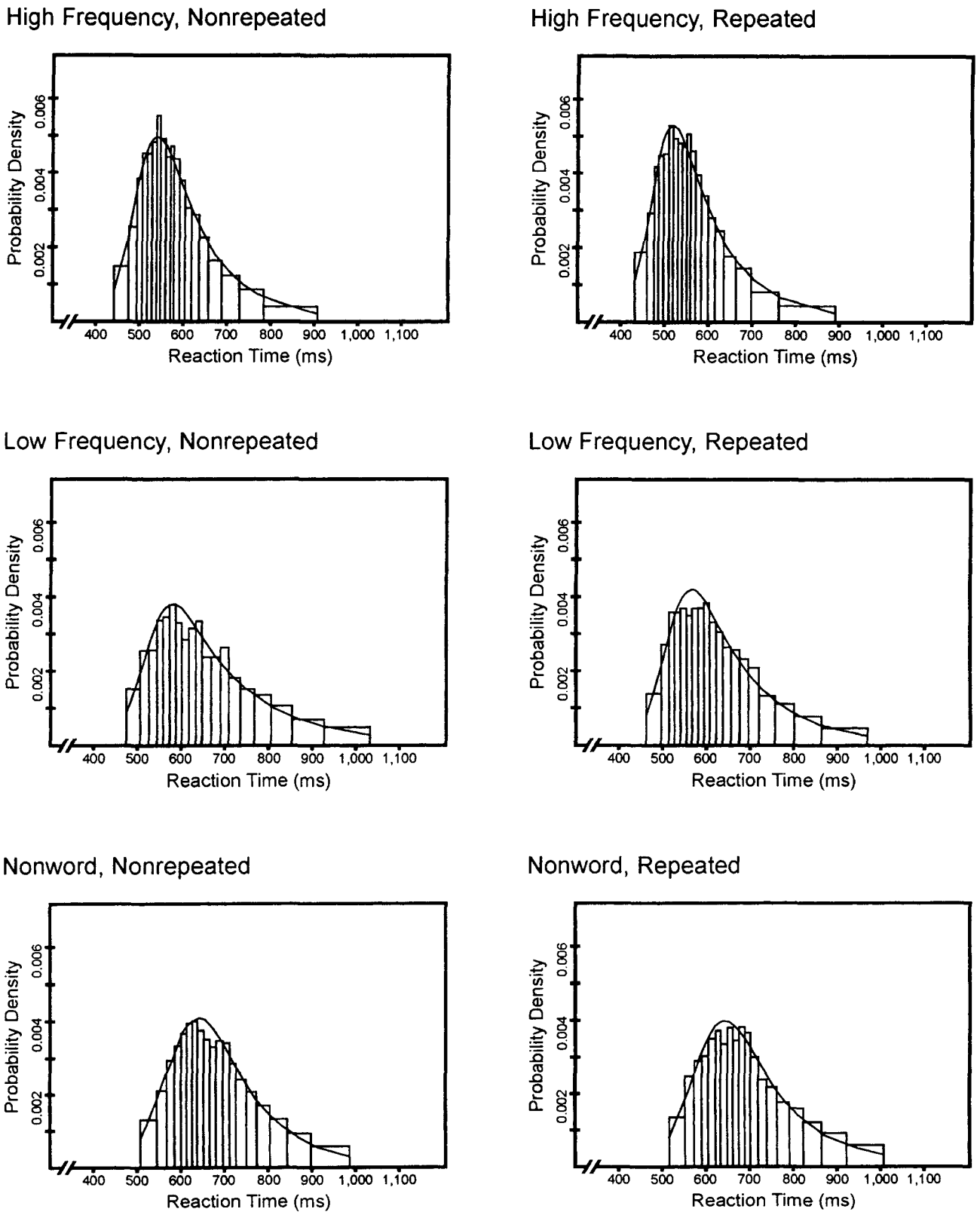

Figure 4. Fit of the ex-Gaussian function to the empirical data from Experiment 1, as a function of frequency, repetition, and lexicality.

Table 2
Means of the Participant's Lexical Decision Means and Means of the Parameter Estimates From the Ex-Gaussian Analyses as a Function of Word-Frequency in Experiment 1

Word frequency	*M*	Mu	Tau	Sigma
High	591	488	103	39
Low	654	517	138	45
Effect	63	29	35	6

of the tail of the distribution for low-frequency words, compared to high-frequency words. The results of the respective ANOVAs yielded a reliable effect of word frequency in the means, $F(1, 47) = 276.23$, $MSE = 691.06$, and in the estimates obtained from the ex-Gaussian analyses of Mu, $F(1, 11) = 58.49$, $MSE = 166.44$, Tau, $F(1, 11) = 31.95$, and Sigma, $F(1, 11) = 6.32$, $MSE = 68.94$.

Thus, there appears to be a relatively large component of the word-frequency effect that occurs in the exponential component of the RT distribution. Clearly, word frequency does not simply shift the RT distribution, but appears to substantially change the shape of the distribution. The relatively large influence of word frequency involved in the exponential component could be viewed as supportive of the notion that at least part of the word-frequency effect in lexical decision performance may be due to an additional attention demanding search process, such as the one proffered by the two-stage model of lexical decision performance.

Repetition × Word Frequency interaction. As noted in the *Introduction*, a number of investigators have reported a larger influence of repetition for low-frequency words than for high-frequency words (e.g., Duchek & Neely, 1989; Forster & Davis, 1984; Scarborough, Cortese, & Scarborough, 1977; Scarborough, Gerard, & Cortese, 1979). The question addressed here is whether this reduction is due to a simple shifting of the RT distributions, or is it due to a change in the shape of the distributions. First, as shown in Table 3, one can see that the means of the high-frequency words (17 ms) produced a smaller repetition effect than the means of the low-frequency words (30 ms), thereby replicating the Frequency × Repetition interaction. More importantly, one can also see that this interaction is primarily carried by changes in Tau, and if anything, there is a slight reversal of the Frequency × Repetition interaction in the estimates of Mu. The results of the respective ANOVAs yielded reliable Frequency × Repetition interactions in both the Means, $F(1, 47) = 6.81$, $MSE = 287.63$, and in the estimates of Tau, $F(1, 11) = 7.12$, $MSE = 149.11$. However, the Frequency × Repetition interaction did not approach significance in either the estimates of Mu, or in the estimates of Sigma, both $Fs < 1.00$.

The RT distribution analyses of the Frequency × Repetition interaction indicate that the reduction in the word-frequency effect is totally due to a decrease in the exponential component for low-frequency words. This is consistent with the argument that repetition may increase the familiarity of low-frequency words more than high-frequency words, and this increase in familiarity may decrease the likelihood of the extra attention-demanding process, which presumably is reflected in the Tau component.

Lexicality × Repetition interaction. As noted in the *Introduction*, one of the intriguing aspects of repetition is the opposite pattern found for words and nonwords. Specifically, a number of studies have reported facilitatory effects of repetition for words (as replicated in the previous section), and *inhibitory* effects of repetition for nonwords (e.g., Duchek & Neely, 1989; Durgunoglu & Neely, 1987; McKoon & Ratcliff, 1979). This pattern was viewed as consistent with the two-stage framework by assuming that the repetition of nonwords increases their familiarity values, thereby increasing the likelihood of nonwords surpassing the lower criterion and engaging the more attention demanding check process. As shown in Table 4, the present results are quite consistent with this account. First, one can see that the results from the means yielded the Lexicality × Repetition interaction in that there is a 24-ms facilitatory effect of repetition for words, and a 11-ms inhibitory effect of repetition for nonwords. Moreover, the inhibitory effect of repetition for nonwords is totally due to a change in Tau. Specifically, there is a 13-ms inhibitory repetition effect for nonwords in Tau, and only a 1-ms facilitatory repetition effect for nonwords in Mu. The results of the respective ANOVAs yielded a highly reliable Lexicality × Repetition interaction in Means, $F(1, 47) = 27.78$, $MSE = 1056.29$, and the estimates from the ex-Gaussian analyses in both Mu,

Table 3
Means of the Participant's Lexical Decision Means and Means of the Parameter Estimates From the Ex-Gaussian Analysis as a Function of Word Frequency and Repetition in Experiment 1

Word frequency/repetition	*M*	Mu	Tau	Sigma
High				
Repeated	583	479	102	37
Nonrepeated	600	497	103	42
Repetition effect	17	18	1	5
Low				
Repeated	639	511	129	43
Nonrepeated	669	523	147	48
Repetition effect	30	12	18	5

Table 4
Means of the Participant's Lexical Decision Means and Means of the Parameter Estimates From the Ex-Gaussian Analysis as a Function of Lexicality and Repetition in Experiment 1

Lexicality/repetition	*M*	Mu	Tau	Sigma
Words				
Repeated	611	495	116	40
Nonrepeated	635	510	125	45
Repetition effect	24	15	9	5
Nonwords				
Repeated	710	577	133	52
Nonrepeated	699	578	120	55
Repetition effect	−11	1	−13	3

$F(1, 11) = 7.98$, $MSE = 143.30$, and in Tau, $F(1, 11) = 9.51$, $MSE = 279.98$, but not in Sigma, $F(1, 11) < 1.00$. Post hoc comparisons of the inhibitory effect observed for the nonwords indicated that this effect occurred in the estimates of Tau, $F(1,11) = 4.90$, $MSE = 381.36$, but not in the estimates of Mu, $F < 1.00$.

Discussion

The results of Experiment 1 are quite clear: The effects of word frequency and repetition do not simply shift the RT distribution to a different location on the time axis, but actually change the shape of the RT distribution. Specifically, the effects of word frequency, the interaction between word frequency and repetition, and the interaction between lexicality and repetition are primarily due to changes in the exponential component of the RT distribution. These results have been interpreted at a descriptive level within a two-stage model in which participants rely on a more nonanalytic familiarity process in the first stage of processing and rely on a more attentional–strategic check process in the second stage of processing.

Although the present distribution results are consistent with the descriptive two-stage model, there are also clearly some inconsistent aspects of the data. We now explore specific ramifications of the results from the ex-Gaussian analyses to better understand how factors and the interaction amongst factors might produce the present results. It is important to note here that the goal of this section is not to test all possible accounts, but rather to provide some insights into the types of accounts that accommodate the present data.

Computational Constraints Imposed by RT Distribution Analyses

Before exploring explicit accounts of the present results, it is necessary to explicitly identify the following major constraints provided by the present data: First, one must obtain parameter estimates of all three components of the ex-Gaussian distribution that have similar characteristics to the obtained data. Specifically, one should be able to produce RT distributions with Mu values around 500 ms, Sigma values around 50 ms, and Tau values around 120 ms. As we shall see, this already imposes considerable constraint on the type of account one can propose. Second, it is important that a model generate RT distributions that are relatively well fit by the ex-Gaussian function, at least as well fit as the actual obtained data.[5] As described below, some models do not produce distributions that are well fit by the ex-Gaussian. Finally, the following effects of factors need to be incorporated into the model: (a) Main effects of word frequency in both Mu and Tau, (b) Main effects of repetition for words in Mu; (c) Word Frequency × Repetition interaction primarily in Tau, and (d) Inhibitory effects of repetition for nonwords primarily in Tau. As we shall see, these constraints strongly limit the class of models that can accommodate these data.

Simple transformations of reaction time distributions. First, one might consider a number of simple transformations to determine if one can identify a way to accommodate the present results. In order to provide specific estimates of such an approach we ran a set of simulations. This was accomplished by first generating a target ex-Gaussian distribution by randomly sampling an RTg from a Gaussian distribution produced by Equation 1 (note the two RNDs in this equation refer to different random numbers), and then adding this RTg to a different randomly sampled RTe from an exponential distribution produced by Equation 2:

$$\mathrm{RTg} = [-2\,log\,(RND)]^{1/2} \cos\,(2piRND)\mathrm{Sigma} + \mathrm{Mu} \quad (1)$$

$$\mathrm{RTe} = -\mathrm{Tau}[log\,(1 - RND)] \quad (2)$$

$$\mathrm{RT} = \mathrm{RTg} + \mathrm{RTe} \quad (3)$$

In this simulation, we produced a distribution which included 2,000 sample reaction times, and, as expected, the generated distribution nicely conformed to an ex-Gaussian distribution that has parameter estimates quite close to the Sigma (60), Mu (600), and Tau (150) used in Equations 1 and 2 to generate the distribution.

Now that we have produced an RT distribution that is well fit by the ex-Gaussian function, we explored the influence of relatively simple transformations to determine if one can differentially influence Mu and Tau, as obtained in the empirical data. Because these are simple atheoretical transformations, we do not distinguish between aspects of distributions that might reflect decisional components versus aspects of the distributions that might reflect non-decisional components. First, consider the simple notion that the effect of word frequency is simply the addition of some constant influence due to the number of exposures to a word. Of course, this is consistent with the implicit assumption that researchers make concerning the effects of variables such as word frequency, that is, the manipulation primarily adds a constant effect size to the distribution. This was accomplished in our simulation by simply adding a constant (50 ms) to each RT generated in the original target distribution. As shown in Table 5, this effect has the desired influence on Mu estimates, but has no influence on Tau estimates. Of course, such an effect is intuitively obvious and the purpose of this simple additive simulation was simply to make explicit the influence of the implicit assumption that researchers make concerning the additive effect of a level of an

[5] It is important to emphasize here that we are not arguing that the RT distributions have to be "ex-Gaussian," but rather that such distributions are well fit by the ex-Gaussian function. This is an important distinction because Van Zandt and Ratcliff (1996) have recently demonstrated that there is considerable similarity amongst a number of candidate distributions such as the Gamma, Weibul, and the ex-Gaussian. In this light, it is important to remember that the ex-Gaussian is currently being used as a tool to understand the influences of manipulations on RT distributions rather than a theoretical claim regarding the underlying reaction time distribution.

Table 5
Single Stage Changes in Parameter Estimates Based on 2,000 Samples of a Target Ex-Gaussian Distribution With Mu = 600 ms, Tau = 150 ms, and Sigma = 65 ms

Original distribution				Transformed distribution		
Mu	Tau	Sigma	Operation	Mu	Tau	Sigma
608	150.4	64	+50 (add.)	660	149	66
608	150.4	64	×1.1 (mult.)	672	167	70
608	150.4	64	∧.98 (expon.)	526	131	53
608	150.4	64	∧.99	558	147	55
608	150.4	64	∧1.01	640	163	64
608	150.4	64	∧1.02	676	181	73

Note. add. = addition; mult. = multiplication; expon. = exponential.

independent variable on reaction time distributions. Second, consider the more interesting possibility that factors produce multiplicative influences on the target RT distributions. This would be consistent with the interpretation of factors that interact within ANOVA designs, that is, the factors produce multiplicative influences. Unfortunately, however, a simple multiplicative transformation again does not accommodate the data, because, as shown in Table 5, all parameter values (Mu, Tau, and Sigma) increase by a constant from such a simplistic single stage model. Thus, again, this would not accommodate the finding that the present data yielded *distinct* effects of variables on the Mu and Tau estimates. Finally, consider the possibility that the influence of frequency, repetition, or both merely change the target distribution in some exponential fashion. This was accomplished by raising each RT observation in the original distribution to powers of .98, .99, 1.01, 1.02 to obtain parameter estimates within the range of the obtained data. Again, as shown in Table 5, such transformations consistently produce changes in all parameters, and, in fact, within this range produced a greater change in Mu than in Tau, which is inconsistent with the present observation wherein certain interactions are localized in Tau, such as the Frequency × Repetition interaction. Thus, power functions also do not allow one to dissociate the influence of manipulations on specific parameter estimates. Of course, there are clearly other simple transformations that one might use to accommodate the present data; however, given the full array of constraints imposed by the present data, we believe that it is unlikely that a simple single transformation can account for these results.

Two-stage models. There are a number of two-stage models that were implemented in an attempt to simulate the present results. The first model implemented was a simple and straightforward interpretation of the two-stage model. This model involved the mixture of two Gaussian RT distributions, one which reflected the relatively fast, more automatic stage, and a second which reflected the slower more analytic stage. This model was implemented in the following manner. In the first stage, a random value was sampled from a normal distribution. This value corresponds to the FM value of the stimulus (see Figure 2). If the FM value was above some predefined threshold, then an RT was selected from a relatively fast Gaussian distribution (presumably reflecting a high-frequency word) with a given Mu (e.g., 500) and Sigma (e.g., 65). On the other hand, if the FM value was below some threshold (as in a low-frequency word), then an additional second stage was engaged. This was implemented by simply adding the value randomly selected from a second Gaussian distribution (reflecting the time course of the second stage) to the value selected in the first Gaussian stage. In our attempt to explore the parameter space of this model, it was very clear that it was failing because in order to obtain the appropriate Tau estimates that were found in the present data (i.e., within the range of 100–150), one would need to have a relatively large influence of the second slower Gaussian distribution. When this was attempted, the resulting RT distribution produced a consistent bimodal form that was not observed in the empirical data. Moreover, the fits of the ex-Gaussian function were relatively poor compared to the actual obtained data. Thus, a relatively straightforward extension of the two-stage model does not account for the present data.

A second two-stage model that was implemented involved the mixing of a Gaussian distribution and an ex-Gaussian distribution. In the first stage of this model, again an FM value was randomly selected from a Gaussian distribution. If the FM value was above a pre-defined upper threshold, an RT was sampled from a Gaussian distribution with a given Mu (550) and Sigma (65). However, if the sampled FM value was below the upper threshold, an RT was sampled from a new distribution that was actually ex-Gaussian in nature, that is, the sum of an RT sampled from a Gaussian distribution (with Mu = 550 and Sigma = 65), and an RT sampled from an exponential distribution (with Tau = 150). The important issue to address now is why the second stage might be exponentially distributed across items. The notion here is that the second stage involves a qualitatively different type of distribution that is exponential in nature. For example, the second stage may involve either a more explicit attempt to directly retrieve the meaning of the stimulus or check the spelling of the stimulus. It is important to note that the engagement of this attention driven retrieval process is likely to be running in parallel with the operations involved in the first stage. However, because attention takes some time to engage (see, e.g., Neely, 1977), the useful output of this process may lag behind the first stage. The notion is that for many items, the

retrieval process produces sufficient information to drive a response once the second stage is engaged. However, for some items, the more attention-based process does not have sufficient information at the time of engagement to drive a response, and so further explicit retrieval is necessary before a response is initiated. The rate of this retrieval is dependent upon the strength of items in memory, which may in large part be frequency dependent. Because as discussed later, one might expect that frequency of occurrence is exponentially related to strength of items in the lexicon, one would expect the completion of this second stage to be exponentially distributed across different items within the list that engage the second stage. In this way, we would suggest that the output from the second stage in the model could take the shape of an exponential function.

Consider how well such a two-stage model accounts for the present results. First, it is noteworthy that in contrast to the mixing of two Gaussian distributions, the mixing of a Gaussian and an ex-Gaussian distribution does a relatively good job of producing an ex-Gaussian distribution, consistent with the empirically obtained RT distributions. More importantly, consider the model's ability to account for the influence of frequency and repetition. Within this model, one might envisage both frequency and repetition as producing a boost in the FM values that are generated by the first normal distribution. In essence, this would be reflected in the mixture of the two distributions. Specifically, a boost in the FM value due to repetition or increased frequency of exposure would decrease the likelihood of an item being below the upper threshold to engage the second stage and hence increase the likelihood that the RT would be generated from the first Gaussian process. Thus, one can test this model by simulating different mixtures of the two distributions by simply changing the threshold used to engage the second stage. Table 6 provides a set of parameters that reflect the likelihood of an FM value surpassing the upper criterion in the two-stage model. For example, if the checking criteria is 1.5 *SD* below the mean then this would produce a mixture such that *most* FM values would engage the second stage (as in a nonrepeated low-frequency word). As one can see, with the Tau values of the present study (i.e., approximately 120), there is little evidence that this model can capture the Word Frequency × Repetition interaction that occurs in Tau, but not in Mu. Specifically, the data indicated that low-frequency words produce a larger influence of repetition in Tau than high-frequency words. However, as shown in the highlighted estimates of Table 6, this is opposite to the general pattern. For example, a .5 *SD* boost in FM due to repetition for a relatively low-frequency word (between 1.0 and .5 *SD* below the mean) produces a 7-ms change in Tau, whereas the same .5 boost in FM due to repetition for a relatively high-frequency word (between 0 *SD* and .5 *SD*s above the mean) produces a 28-ms change in Tau. In this light, it would appear that repetition has a larger effect on high-frequency words than low-frequency words in the Tau parameter, and if anything, as shown in this table there is some evidence that the interaction actually occurs in changes in Mu. Of course, one may be able to modify the values of Sigma and Tau to change the mixing probabilities. However, when this was attempted, there was considerable breakdown in how well the ex-Gaussian model fits the obtained data. Thus, the complex constraints imposed by the present data again appear to pose difficulties for another class of two-stage models.

Hybrid two-stage model. Given the above difficulties in implementing a simple model to account for the present results, an attempt was made to re-evaluate the approach. The dissociation of effects of variables on Mu and Tau suggests that different processes may be influencing different parameters in the RT distributions. Interestingly, there does appear to be evidence in the literature that frequency effects and their interactive influences with repetition in lexical decision performance may also be composed of two distinct processes. Specifically, the work by Forster and Davis (1984), Rajaram and Neely (1992), Segui and Grainger (1990), and Sereno (1991) has indicated that the Frequency × Repetition interaction is eliminated under conditions in which the first presentation of the prime is masked and is

Table 6
Changes in the Parameter Estimates Due to Differences in Mixtures of the Gaussian Distribution First Stage and the Exponential Distribution Second Stage

Checking criteria condition in *SD* units from *M*	Mu	Tau	Sigma	Example
−2.5	549	153	61	
−2.0	547	153	58	
−1.5	538	150	59	
−1.0	**528**	**146**	**56**	LF nonrepeated
−0.5	**513**	**139**	**52**	LF repeated
0.0	**499**	**123**	**45**	HF nonrepeated
.5	**499**	**95**	**49**	HF repeated
1.0	499	73	46	
1.5	507	51	50	
2.0	512	43	51	
2.5	521	32	53	

Note. Boldface indicates comparisons discussed in text. LF = low frequency; HF = high frequency.

presumably available only to limited, if at all, conscious processing. Forster and Davis have suggested that this pattern may be due to an explicit episodic contribution to the typical Frequency × Repetition interaction (see, however, Rajaram & Neely, 1992). Specifically, there is evidence that episodic recognition is actually better for low-frequency words than for high-frequency words (e.g., Balota & Neely, 1980; Glanzer & Bowles, 1976), and it may be the case that this episodic contribution is also producing the Word Frequency × Repetition interaction in lexical decision performance that one typically finds for unmasked presentations of stimuli. When one masks the first presentation of the stimulus, thereby limiting episodic processing, one actually eliminates the interaction and finds main effects of repetition and frequency. Thus, it is possible that there are two distinct processes that are modulated by word frequency and repetition. One process may be more automatic in nature, occurs under highly masked conditions, and produces additive effects of word frequency and repetition. The second process may be more attentional in nature, occurs under unmasked conditions, and produces interactive influences of word frequency and repetition. This distinction also nicely parallels the present results. Specifically, both repetition and word frequency produce additive effects on the aspect of the RT distribution that may reflect more automatic processes (Mu), whereas, these factors produce interactive effects on the component of the RT distribution that reflects the more attention demanding processes (Tau). We now turn to an explicit attempt to model such a pattern.

The hybrid two-stage model was implemented in the following manner: First, as in the original two-stage model, a normal distribution was generated, and an FM value was sampled from this distribution. If the FM value was above the mean of the FM distribution, then an RT was generated from a Gaussian distribution, with specified Mu and Sigma values. (Sigma was set at 60 for all of the Gaussian distributions that generate RTs from the first stage.) If the FM value generated was below the mean of the FM distribution, then the second exponential stage of the model was engaged and the resultant RT was generated from an ex-Gaussian distribution, with specified Mu, Sigma, and Tau values. (Tau was set at 150 for the exponential component of the second stage.) Thus, the resulting distribution reflects a mixture of Gaussian and ex-Gaussian distributions that, as noted above, nicely produce distributions that are well-captured by the ex-Gaussian function.

Consistent with the extant literature indicating additive effects of frequency and repetition under more automatic masked priming conditions, and interactive effects of frequency and repetition under unmasked episodic attentional priming conditions, the influence of these variables were implemented in two distinct ways in the hybrid two-stage model. First, consider the more automatic influence of repetition and frequency. This was implemented simply by shifting the mean of the Gaussian distributions used to generate RTs in the first stage of the model by .5 *SD*s and .17 *SD*s for frequency and repetition, respectively. As described above, and demonstrated in Table 5, this ultimately has the effect of adding a constant to the distribution and should only produce an effect in Mu. Now, consider how the second more attentional–episodic influence was implemented in the hybrid two-stage model. Consistent with the original two-stage model, this was accomplished by shifting the FM value by a constant of .83, .50, .20, and −.80 *SD*s for high-frequency repeated, high-frequency nonrepeated, low-frequency repeated, low-frequency nonrepeated items from the mean of the original Gaussian distribution used to generate FM values. As one can see by the selected values, the FM values were on average higher for high-frequency words (.67 *SD*s above the mean) than low-frequency words (−.30 below the mean), and the influence of repetition was greater for low-frequency words (1.0 *SD*) than for high-frequency words (.33 *SD*). The larger boost in the FM values for low-frequency words than for high-frequency words is motivated by the extant literature indicating (a) that low-frequency words are better recognized in episodic memory tasks than are high-frequency words, and (b) the interactive effects of repetition and word frequency in an unmasked primed lexical decision task. Of course, given a constant upper criterion, these shifts in the FM values as a function of frequency and repetition primarily modulated the probabilistic mixing of RTs that were produced from the first stage (Gaussian distributed) and those that also included the second exponentially distributed stage. Because the second stage of the model involves an exponential component, these shifts in FM values primarily should modulate the Tau component of the resulting RT distributions.

Figure 5 displays the fits of the ex-Gaussian function to the data generated by the hybrid two-stage model, as a function of frequency, repetition, and lexicality. As shown, the fits appear to be relatively good overall, although there is some deviation in modal portions of the fits, especially for the high-frequency repeated condition. Interestingly, there also appears to be a similar deviation (albeit smaller) in the high-frequency repeated condition in the empirical data, compare Figures 4 and 5. We shall now turn to a direct evaluation of the parameter estimates.

Table 7 displays the resulting parameter estimates for both word frequency and repetition that were simulated on the basis of the average of 3 runs of 2,000 observations per run with the above specified parameters. There are two important points to note in Table 7. First, as one can see, there is evidence of a main effect of both word frequency and repetition in Mu. Second, one finds that the Frequency × Repetition interaction occurs primarily in Tau. Moreover, by comparing Table 7 with Table 3, one can see that not only does the model capture the important patterns in the data, but the actual parameter values are quite close to the empirical data.

Now, consider the Lexicality × Repetition interaction. As shown in Table 4, and consistent with the extant literature, words benefited from repetition, whereas, nonwords were actually slowed by repetition. Moreover, the deleterious effect of repetition for nonwords was totally in the Tau component. How might this be accommodated within the hybrid two-stage model? Here, one might argue that because nonwords do not have a preexisting lexical representation that the shift in the central tendency of the first Gaussian

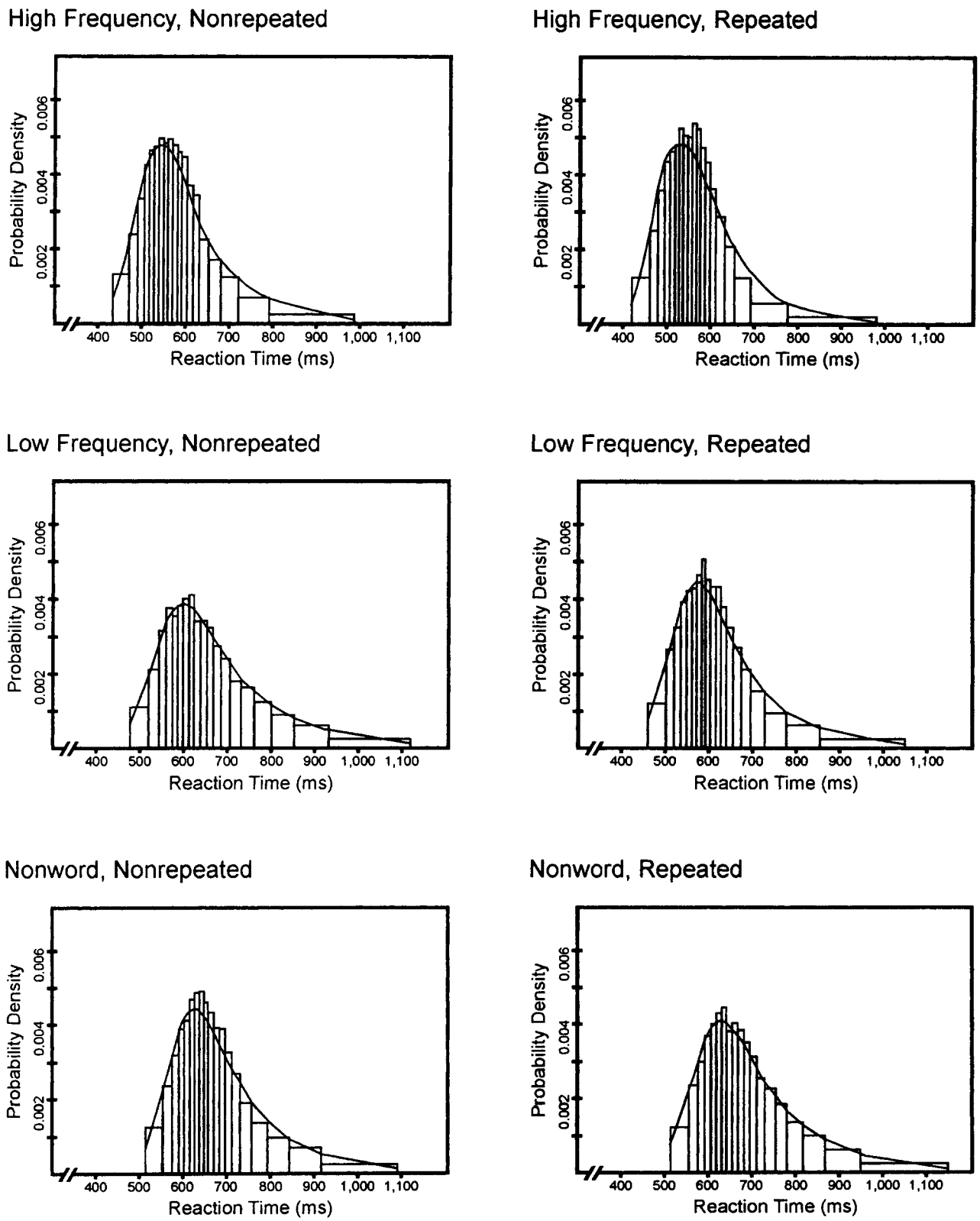

Figure 5. Fit of the ex-Gaussian function to the simulations from the hybrid two-stage model as a function of frequency, repetition, and lexicality.

Table 7
Mean Parameter Estimates for the Hybrid Model for the Word Frequency × Repetition Interaction

Word frequency/repetition	*M*	Mu	Tau	Sigma
High				
Repeated	587	485	102	45
Nonrepeated	606	499	107	47
Repetition effect	19	14	5	2
Low				
Repeated	635	517	118	47
Nonrepeated	679	537	142	52
Repetition effect	44	20	24	5

Note. Estimates are based on three runs with 2,000 sample response times per run.

component due to the effect of repetition on the fluency-based operations should not be implemented for nonwords. In fact, Forster and Davis (1984) found small and inconsistent repetition effects for nonwords under masked priming conditions (see, however, Bodner & Masson, 1997). Thus, for nonwords, one might simply expect a change in the likelihood of sampling from the second stage, because of the episodic–attentional contribution. This was accomplished by simply boosting the FM value generated for the nonword distribution by .42 *SD*s due to repetition. As in the original two-stage model, a boost due to an increase in familiarity for nonwords, increases the likelihood of sampling from the second exponential stage, that is, increases the likelihood of surpassing the *lower* criterion which was centered about the mean of the distribution producing the FM values for nonrepeated nonwords. As shown in Table 8, the model again accommodates the obtained data. Specifically, the boost in FM values for nonwords with a constant lower criterion produces an inhibitory effect of repetition which is localized in Tau.

In sum, the present section has indicated that there are a number of assumptions that one needs to make to account for the constraints that are available in the present data. Simple arithmetic changes in the distributions, and simple two-stage accounts were unable to account for the present pattern of results. However, the present modeling endeavor was successful when considered in light of the extant literature indicating that the conjoint effects of frequency, repetition, and lexicality are quite different under conditions which limit attention processing (masked priming), compared to a condition which allows a more episodic–attentional contribution (unmasked priming). Of course, we would not argue that the present account is the only account of these data, but rather would argue that the ex-Gaussian analyses provides important insight to the types of models that one might need to account for these results. However, we should note that the present assumptions are also consistent with extant empirical evidence regarding the distinct influences of repetition on high- and low-frequency words and nonwords under masked and unmasked priming conditions. We explore the implications of this observation later after the results from a different task are presented.

Table 8
Means of Hybrid Model Parameter Estimates for the Lexicality × Repetition Interaction

Lexicality/repetition	*M*	Mu	Tau	Sigma
Words				
Repeated	611	501	110	46
Nonrepeated	643	518	125	50
Repetition effect	32	17	15	4
Nonwords				
Repeated	708	574	134	49
Nonrepeated	690	569	121	47
Repetition effect	−18	−5	−13	−2

Note. Estimates are based on three runs with 2,000 sample response times per run.

Experiment 2

The present discussion has emphasized the task-specific operations involved in the lexical decision task. However, it is quite possible that the same pattern of effects of the targeted variables would occur in the other major task used to study word recognition performance, speeded naming. If this were the case, then one would need to reevaluate the present emphasis on distinct components that are tied to the lexical decision task. Thus, in Experiment 2, we replicate the design of Experiment 1 with the only difference being that participants were asked to name each stimulus aloud in Session 2 instead of making lexical decisions. If the effects in the exponential component in Experiment 1 are related to the emphasis on the discrimination between familiar words and unfamiliar nonwords engaged in the lexical decision task, then one should expect that this pattern of effects should be quite different in a task in which participants are not required to make such a discrimination (i.e., a speeded naming task).

Method

Participants. A total of 48 participants were recruited from undergraduate courses at Washington University. The mean age of these individuals was 22.1 years.

Apparatus. A Gerbrands G1341T voice-operated relay was interfaced with the same apparatus used in Experiment 1 to obtain onset latencies.

Materials. The materials and counterbalancing procedure were identical with Experiment 1.

Procedure. There were two differences in Experiment 2, compared to Experiment 1: First, participants named each stimulus word aloud as quickly and as accurately as possible in Phase 2 instead of pressing buttons to make word–nonword discriminations. Second, participants coded their own responses after each stimulus was named. Specifically, after the onset of the pronunciation triggered erasure of the screen, participants were presented with a message indicating to press the "1" button on the keyboard if any inappropriate sound triggered the voice key (e.g., a mispronunciation or extraneous sound such as a cough), and press the "0" button if the correct pronunciation triggered the offset of the display. Participants were given practice before the experiment began in coding their responses.

Table 9
Mean of the Participant's Naming Latency Means and Means of the Parameter Estimates From the Ex-Gaussian Analyses as a Function of Word Frequency in Experiment 2

Word frequency	*M*	Mu	Tau	Sigma
High	541	466	74	51
Low	553	476	75	56
Effect	12	10	1	5

Results

The analyses were precisely the same as in Experiment 1. The mean outlier rate and mean percentage of trials that were eliminated because of extraneous sounds triggering the computer were 1% and 2%, respectively.

Word-frequency effects. The effects of word frequency on the estimates are displayed in Table 9. The first point to note is that the word-frequency effects are overall much smaller in naming (12 ms) than in the earlier lexical decision (63 ms) experiment. One might expect this decrease in the word-frequency effect if part of the word-frequency effect in the earlier lexical decision task is due to a premium placed on frequency–familiarity-based information. Moreover, it appears that word frequency influences the distribution differently in naming than in lexical decision performance. Remember that in lexical decision performance the word-frequency effect occurred in both estimates of Mu and Tau, whereas, in the naming study, there appears to be only an influence in Mu (10 ms) with virtually no influence in Tau (1 ms). The results of the respective ANOVAs supported this observation, with a reliable influence of word-frequency effect in the means, $F(1, 47) = 19.96$, $MSE = 342.60$, and in the estimates of Mu, $F(1, 11) = 7.56$, $MSE = 164.41$. However, the word-frequency effect in Tau did not approach significance, $F(1, 11) < 1.00$. The word-frequency effect in Sigma was also not significant, $F(1, 11) = 2.78$, $MSE = 134.43$. Thus, the results are consistent with the prediction that naming performance should produce less of a frequency effect in the exponential component compared to lexical decision performance.

Word Frequency × Repetition interaction. Table 10 displays the effects of repetition as a function of word frequency. *A priori*, one would have expected a larger repetition effect for low-frequency words than for high-frequency words, as found in Experiment 1. However, the pattern displayed in Table 10 is not consistent with this prediction. First, as shown in Table 10, there is a relatively small repetition effect in naming, compared to lexical decision performance. Moreover, this effect is slightly, at least numerically, larger for high-frequency words than low-frequency words. This pattern is primarily carried in the estimates of Tau, with a slight negative influence of repetition in the estimates of Mu. The results from the respective ANOVAs yielded a reliable effect of repetition in the means, $F(1, 47) = 8.17$, $MSE = 309.20$, and in the estimates of Tau, $F(1, 11) = 6.78$, $MSE = 297.32$. Neither the repetition effect in the estimates of Mu nor in the estimates of Sigma approached significance, both $Fs(1, 11) < 1.63$. None of the analyses yielded any evidence of a reliable Frequency × Repetition interaction, all $Fs(1, 11) < 2.75$, and, as noted, there was slightly more of a repetition effect for the high-frequency words than for the low-frequency words.

The results of the naming task produce a different pattern concerning frequency and repetition than the earlier lexical decision task. Repetition appears to be influencing both high- and low-frequency words in a similar fashion in Experiment 2. As discussed below, we believe that the lack of a Frequency × Repetition interaction in the naming data may be related to the lack of a word-frequency effect in the rhyming task. However, we shall postpone discussion of this issue until the data from the rhyme task are presented.

Lexicality × Repetition interaction. Table 11 displays the repetition effects as a function of lexicality. As shown in the means of Table 11, both words (7 ms) and nonwords (5 ms) benefited to a similar, but small, degree from repetition. Moreover, this effect of repetition is not due to a shift of the distribution as would be reflected in a shift in Mu, but rather is due to a decrease in the exponential component of the distribution, as reflected by a reduction in Tau. The results of the respective ANOVAs indicated that there was a reliable main effect of repetition in the means, $F(1, 47) = 5.87$, $MSE = 590.56$, with the estimate of Tau approaching significance, $F(1, 11) = 4.08$, $MSE = 486.70$, $p < .10$. However, there was no evidence of a repetition effect in the

Table 10
Means of the Participant's Naming Latency Means and Means of the Parameter Estimates From the Ex-Gaussian Analysis as a Function of Word Frequency and Repetition, in Experiment 2

Word frequency/repetition	*M*	Mu	Tau	Sigma
High				
Repeated	536	470	65	54
Nonrepeated	545	462	83	47
Repetition effect	9	−8	18	−7
Low				
Repeated	550	478	71	58
Nonrepeated	555	475	79	55
Repetition effect	5	−3	8	−3

Table 11
Means of the Participant's Naming Latency Means and Means of the Parameter Estimates From the Ex-Gaussian Analysis as a Function of Lexicality and Repetition in Experiment 2

Lexicality/repetition	*M*	Mu	Tau	Sigma
Words				
Repeated	543	474	68	56
Nonrepeated	550	469	81	51
Repetition effect	7	−5	13	−5
Nonwords				
Repeated	590	493	96	59
Nonrepeated	595	493	102	60
Repetition effect	5	0	6	1

estimates of Mu or Sigma, both $Fs < 1.00$. Finally, none of the ANOVAs yielded any evidence of a Repetition × Lexicality interaction, all $Fs < 2.10$.

In contrast to the results of the lexical decision task, wherein there was evidence of an inhibitory influence of repetition for nonwords, the present naming results yielded an equally beneficial effect of repetition for both words and nonwords.

Discussion

The naming results of Experiment 2 are in sharp contrast to the lexical decision results of Experiment 1. Most interesting is the observation that there was no influence of word frequency on the estimate of exponential component in the naming task, but only in the estimate of the mean of the Gaussian component. Moreover, the results of Experiment 2 provided no hint of the Frequency × Repetition or Lexicality × Repetition interactions that were obtained in Experiment 1. These results support the contention that the types of processes that are engaged by the two tasks are quite distinct. The task specific processes not only modulate the influence of factors on the means differently but also influence the shapes of the RT distributions differently.

Experiment 3

One possible constraint on the interpretation of the word-frequency effects obtained in Experiment 2 is that the word-frequency effect was diminished because of the presence of nonwords. For example, Monsell, Patterson, Graham, Hughes, & Milroy (1992) have suggested that the presence of the nonwords might encourage the use of a separate sublexical route that converts spelling patterns into speech patterns in the naming task, and thereby encourage participants to bypass the more lexically mediated route (see, however, Lupker, Brown, & Colombo, 1997, for an alternative interpretation). Moreover, it is possible that participating in a rhyme task during Phase 1 also encouraged participants to rely on a sublexical process that converts the spelling patterns into phonological patterns necessary to make the rhyme decisions. In order to address these possibilities, we conducted Experiment 3 in which we eliminated the rhyme phase, and also eliminated the nonwords. We expected that the effects of word frequency would increase in this experiment. The more important question is whether one will now find word-frequency effects primarily in the Mu component, as observed in the naming results of Experiment 2, or in both the Mu component and the Tau component as observed in the lexical decision results of Experiment 1.

Method

Participants. A total of 20 participants were recruited from undergraduate courses at Washington University. The mean age of these individuals was 21.3 years.

Materials and procedure. The same word targets used in the previous experiment were used in this experiment. All participants only received the naming phase of the experiment, and named the target stimuli with the same procedures used in Experiment 2. The total experiment lasted approximately 30 min.

Results

The analyses were the same as those used in Experiment 2. The mean percentage outlier rate and the mean percentage of trials that were screened because of extraneous triggering of the voice key were 1.0% and 0.1%, respectively.

Because each level of word frequency included 80 observations per participant, we were able to Vincentize and create super subjects across sets of two participants, instead of sets of four participants used in the previous two experiments.

The results of Experiment 3 are displayed in Table 12. As predicted, the word-frequency effect (18 ms) is larger than the naming results of Experiment 2 (12 ms), but is still not nearly as large as the word-frequency effect obtained in the lexical decision results of Experiment 1 (63 ms). More importantly, the results of Experiment 3 again indicate that the effect of word frequency in naming performance with this set of stimuli is primarily in changes in Mu. The results of the ANOVAs yielded a reliable 18-ms frequency effect in the means, $F(1, 19) = 34.36$, $MSE = 98.31$, and an 18-ms effect in the estimates of Mu, $F(1, 9) = 6.21$, $MSE = 278.97$. However, there was no evidence of a word-frequency effect in Tau (0 ms) nor in Sigma, both $Fs < 1.05$.

In sum, the results of Experiment 3 replicate the pattern observed in Experiment 2. Although the word-frequency effect is larger, the effect of word frequency is again primarily in the shifts in the central tendency of the Gaussian component. We shall now turn to an analysis of the Phase 1 rhyme data for both Experiments 1 and 2.

Analyses of the Rhyming Data

In both Experiments 1 and 2, participants made speeded rhyme decisions to both words and nonwords during Phase 1. The rhyme task was chosen as an orienting task because we did not wish to contaminate the decisions–responses during the first and second presentations of the stimulus. In this way, we were able to address relatively pure effects of stimulus repetition during Phase 2. However, there are a number of intriguing aspects of the rhyme sessions with respect to word frequency and with respect to characteristics of the RT distributions. Because both experiments were identical with respect to the rhyme sessions, we present the two experiments together. However, it is important to note here that an overall analysis which included Experiment as a

Table 12
Mean of the Participants Naming Latencies and Mean of the Estimates From the Ex-Gaussian Analyses as a Function of Word Frequency for Experiment 3

Word frequency	*M*	Mu	Tau	Sigma
High	523	464	59	48
Low	541	482	59	52
Effect	18	18	0	4

factor did not yield any main effects or interactions that included this factor.

There were two sets of analyses conducted on the rhyme data. First, because there were 20 observations that were produced by the factorial crossing of response (rhyme vs. nonrhyme), lexicality (word vs. nonword), and frequency (high vs. low), we collapsed across response in one set of analyses to produce 40 observations per participant cell, and collapsed across frequency in the second set of analyses which again produced the targeted 40 observations per participant cell. After collapsing across these factors, super-subjects were produced by Vincentizing and again the respective ANOVAs were conducted.

The mean error rate and outlier rate were 4% and 2%, respectively.

Word-frequency effects. The effect of word frequency on rhyme decisions are displayed in Table 13. As shown in this table, there is no evidence of a word-frequency effect in either the means or in any of the parameter estimates, all $Fs < 1.00$, on the basis of analyses of only the word data. This pattern is in considerable opposition to the results of Experiments 1, 2, and 3, wherein there were highly reliable effects of word frequency with the same set of stimuli. Thus, these results appear to indicate that participants are relying on a frequency-independent code to make their rhyme decisions. This pattern could be viewed as consistent with the notion that in making rhyme decisions to both words and nonwords, that participants may direct attention to a sublexical mapping of spelling to sound, and therefore not rely on a lexical code which is modulated by word frequency (see Balota & Ferraro, 1996, for further discussion). Interestingly, a number of dual-route advocates have suggested that the sublexical code is not modulated by whole word frequency (cf. Coltheart, 1978; Monsell et al., 1992; Paap & Noel, 1991). The present results could be viewed as supportive of this perspective. At the very least, these results suggest that the influence of word frequency appears to be highly task dependent.

Response × Lexicality interactions. Table 14 presents the means and estimates of the parameters from the ex-Gaussian analyses as a function of Response (Rhyme vs. Nonrhyme) and Lexicality. There are three patterns of data that are particularly noteworthy in this table. First, there is evidence of a main effect of lexicality in the means, with words producing 30-ms faster rhyme decisions than nonwords, $F(1, 94) = 82.12$, $MSE = 1700.12$. Interestingly, this effect of lexicality in means is primarily driven in the estimates of Tau, $F(1, 22) = 79.96$, $MSE = 324.14$, with no effect of lexicality in the estimates of Mu or Sigma. Second, mean response latencies to rhyming pairs are 51 ms faster than to nonrhyming pairs, $F(1, 94) = 94.25$, $MSE = 5130.54$. However, in contrast to the effect of lexicality, this effect is totally carried by a change in Mu, $F(1, 22) = 83.031$, $MSE = 967.40$, with no reliable effect of rhyme decision in either the estimates of Tau, $F(1, 22) = 2.85$, $MSE = 421.58$, $p > .10$, or in the estimates of Sigma, $F < 1.00$. Clearly, response and lexicality are having strong influences on performance and are modulating considerably different characteristics of the RT distribution. Third, as shown in Table 14, there is evidence that the benefit of words over nonwords is larger for rhyming pairs than for nonrhyming pairs, $F(1, 94) = 20.22$, $MSE = 1524.58$. Interestingly, this interaction is totally carried by changes in the estimates of the Mu component with no evidence of an interaction in the estimates of Tau or Sigma, both $Fs < 1.00$.

In sum, there are two intriguing aspects of the results from the rhyme task. First, there is no hint of an effect of word frequency for the same set of stimuli that produced large word-frequency effects in the lexical decision task and smaller, but highly reliable, word-frequency effects in the naming experiments. Second, the relatively large effects of lexicality and rhyme decision that occurred in the analyses of the means were produced by different components of the RT distributions. Specifically, the influence of lexicality was totally modulated by changes in Tau, while the influence of response was totally modulated by changes in Mu. This dissociation highlights the importance of considering changes in the shape of the RT distribution, as opposed to only considering changes in estimates of central tendency of the response distribution.

Table 13
Mean of the Participant's Rhyme Decision Latencies and Mean of the Participant's Parameter Estimates From the Ex-Gaussian Analyses as a Function of Word Frequency

Word frequency	*M*	Mu	Tau	Sigma
High	679	553	125	68
Low	681	550	129	70
Effect	2	−3	4	2

Table 14
Means of the Participant's Rhyme Decision Latencies and Means of the Parameter Estimates From the Ex-Gaussian Analysis as a Function of Response and Lexicality for Both Experiments 1 and 2

Response/lexicality	*M*	Mu	Tau	Sigma
Rhyming pairs				
Words	648	515	133	55
Nonwords	690	522	168	58
Lexicality effect	42	7	35	3
Nonrhyming pairs				
Words	711	582	130	56
Nonwords	728	570	158	55
Lexicality effect	17	−12	28	−1

General Discussion

There are three noteworthy aspects of the present results. First, and most importantly, the influence of both word frequency and the within-experiment repetition of words and nonwords do not consistently produce shifts in the RT distribution, but rather change the shapes of the RT distributions. Second, word frequency and repetition of words and nonwords changed the shapes of the RT distributions differently in naming and lexical decision tasks. Third, the

analyses of the rhyming task yielded a dissociation between the effects of lexicality and response such that the influence of lexicality on the means was totally due to an increase in the tail of the RT distribution, whereas, the influence of response on the means was totally due to a shift in the RT distribution. We shall now turn to a discussion of the theoretical implication of these observations.

Word-Frequency Effects in Lexical Decision and Word Naming

One of the intriguing aspects of the present results is that a large portion of the word-frequency effect in the lexical decision task was in the exponential component (Tau), whereas, in the word-naming task (with the same set of stimuli), the word-frequency effect was only in the central estimate of the Gaussian component (Mu). The lexical decision results replicated a recent pattern reported by Plourde and Besner (1997) and the naming results were replicated in the present study (Experiment 3). These results initially appeared to be consistent with the two-stage model of lexical decision performance developed by Balota and Chumbley (1984). The notion is that word-frequency effects may be exaggerated in the lexical decision task because participants are likely to engage in an extra more attention demanding check process for low-frequency words compared to high-frequency words. This additional check process is presumably a reflection of the type of discrimination that participants are required to make in the lexical decision task (i.e., discriminate familiar words from unfamiliar nonwords). Because low-frequency words are less familiar than high-frequency words these items are more difficult to discriminate from nonwords, and so are more likely to engage an additional check process. Moreover, because naming performance does not demand the same type of discrimination process to drive the response (i.e., between familiar words and unfamiliar nonwords), there is a decreased likelihood of the same type of analytic check process, and so the effect of word frequency may be more likely to occur in shifts of the reaction time distribution in the naming task.

The present study has focused on specific operations that are engaged by the lexical decision task in accounting for the influence of repetition and word frequency on the different components of reaction time distributions. We have emphasized the lexical decision results because of an explicit theoretical framework that a priori appeared to make different predictions concerning distinct aspects of the reaction time distributions. Given the present pattern of results, one might be led to argue that the naming task is the same as lexical decision, but without the decision component. We clearly do not believe that this is the case. We would argue, however, that, compared to the naming task, lexical decision places a higher demand on both frequency and familiarity due to the nature of the discrimination that is involved in this task. Likewise, we should emphasize here that we are not arguing that frequency effects will always simply shift the distribution in naming without an accompanying change in the exponential component. Clearly, this depends on the particular set of stimuli that appear in the high- and low-frequency conditions. The important observation in the present study is that for the *same* relatively large set of stimuli, one finds distinct influences of frequency, repetition, and lexicality on the shape of the reaction time distributions across lexical decision and naming performance. Although the present analyses of the RT distributions for naming performance have relevance to extant models of naming performance (e.g., Plaut et al., 1996), we now turn to a more focused discussion of these results for the two process models of lexical decision performance that were directly explored in this article.

Two-Process Models of Lexical Decision Performance

Although as noted earlier, the results are consistent with aspects of the two-stage model, the present results also clearly produced some inconsistencies with this model. First, as indicated in the modeling section, a relatively straightforward implementation of the model in which the observed reaction time distribution consists of a Gaussian distribution and a probabilistic mixture of a second Gaussian distribution (reflecting the second analytic check stage), produced reaction time distributions that were bimodal in nature and were not well fit by the ex-Gaussian function. We then attempted to implement a model that involved a mixture of trials which included samples from a Gaussian distribution (reflecting the first stage), and trials which also included samples from an exponential distribution (reflecting the second attention demanding check stage involving the explicitly retrieved information from memory). The resulting distribution was well-fit by the ex-Gaussian distribution with parameter estimates that were quite similar to the obtained data. Unfortunately, however, this model also produced some problems. For example, the present results yielded main effects of both word frequency and repetition in Mu. Neither of these effects were predicted by the model. Moreover, this model failed to accurately capture the larger repetition effect for low-frequency words than for high-frequency words that was totally in Tau.

In order to address these limitations, we developed a hybrid two-stage model which involved separable effects of frequency and repetition on the first stage and on the second more analytic stage. This hybrid model was motivated by existing evidence which suggests that there are quite distinct influences of repetition and word frequency under masked automatic processing conditions and unmasked more attentional processing conditions (e.g., Forster & Davis, 1984). In this light, the distinct manner in which frequency and repetition modulate Mu and Tau appear to be compatible with the view that repetition produces distinct and separable influences in lexical decision performance. One effect occurs under unmasked conditions, interacts with word frequency, and is more attention demanding. This effect produces interactive effects in the slower tail of the distribution, that is, in Tau. The second effect occurs under masked conditions, is more automatic in nature, and produces main effects in Mu. In this light, the ex-Gaussian analysis provides converging support for the arguments regarding the locus of repetition, word frequency, and lexicality effects in masked and unmasked prime conditions in lexical decision

performance (see Forster & Davis, 1984). Moreover, the implementation of these two distinct types of repetition effects within a hybrid two-stage model accommodated the major effects of these variables in the reaction time distributions.

Limitations to the Hybrid Two-Stage Model

There are some limitations to the hybrid two-stage model. First, although there was (a) little evidence of speed accuracy tradeoffs in the present data (see Balota & Ferraro, 1996, for further details), and (b) error rates were relatively low, the current model was not extended to error rates and error latencies. Unfortunately because of the relatively low error rate and the multiple potential causes of such errors (e.g., momentary forgetting which keys correspond to word and nonword, error in early perceptual analyses, or possibly temporal deadline being reached), it would be difficult to provide a strong test of the current model with the standard lexical decision task. In this light, it would be useful to combine the present ex-Gaussian analyses with future studies which directly investigate both speed and accuracy using response deadline procedures (see, e.g., Hintzman & Curran, 1997). Thus, although the present modeling endeavor goes beyond the standard estimates of central tendency to make predictions regarding the nature of response latency distributions, there are further important aspects of lexical decision behavior that need to be explored in future implementations.

Second, for purposes of simplicity, we assumed that the response latencies generated during the first stage were normally distributed. However, an interesting alternative model that also fits the data is the mixture of an ex-Gaussian distribution with a relatively fast exponential component (reflecting the first stage) and an ex-Gaussian distribution with a relatively slow exponential component (reflecting the second stage). The mixtures of two ex-Gaussian distributions produces a distribution that is fit quite well by a single ex-Gaussian function. The major difference between this model and the hybrid model explored in this article is the presence of an exponential component during Stage 1. Thus, in some sense, the current implementation is the limiting case of a class of such models in which the first exponential component during Stage 1 is set to zero. Of course, the inclusion of an exponential component during Stage 1 increases the predictive power of this class of two-stage models, and ultimately may be more faithful to the temporal characteristics of cognitive operations.

Alternative Accounts of the Present Distribution Results

Although the hybrid two-stage model is compatible with the set of constraints imposed by the present data, there are alternative frameworks that might also predict these results. Such predictions depend upon the specific characteristics of a given model and how frequency maps onto changes in RT at an item level. First, consider a logogen-type framework that maps the frequency of exposure to resting level thresholds in the manner displayed in Figure 6. If one considers a given high-frequency range between 50 and 100 counts per million in this figure, there is relatively little variability in the resting level thresholds that presumably determine the speed of word recognition. On the other hand, if one now selects a smaller frequency range between 0 and 10 counts per million, one might expect considerably more variability in the distribution of resting level activation. Moreover, given the variability in the participant population in exposure to low-frequency words, there might be an increased likelihood of some low-frequency items falling in the tail of the distributions. Thus, because of the increase in the sensitivity of the resting thresholds to word frequency at the lower end of the frequency range, it is possible that a simple logogen type model would also predict a larger Tau component for low-frequency words than for high-frequency words. (Similar predictions might arise from serial search models, hybrid models, and more recent connectionist models.) Interestingly, a logogen-type model might also predict an interaction between frequency and repetition simply because of the fact that the resting level activation for high-frequency words may be at a functional ceiling and would no longer benefit from repetition. As shown in Figure 6, the change in resting level activation as a function of repetition is greater for low-frequency words than for high-frequency words. Because of the increased variability and sensitivity to frequency at the lower-end of the activation–frequency function, one might expect repetition to primarily influence the tail of the low-frequency distribution. Although a logogen model may be able to descriptively accommodate the present results there are a number of difficulties that one would need to overcome that we encountered in implementing two-stage models. For example, it is unclear if such a model would produce (a) the types of response distributions (i.e., similar estimates of Mu, Tau, and Sigma) that are actually observed, (b) the interactive effects of frequency and repetition in Tau, and the main effects of these variables in Mu, and (c) the inhibitory effects of repetition for nonwords only in Tau. In this light, we would argue that the analysis of RT distributions affords a more direct test of the predictions from models of word recognition than estimates of central tendency. Moreover, we would also argue that because variables appear to modulate different parameters of the RT distributions across lexical decision and naming, any adequate model of word recognition performance based on these tasks must incorporate sensitivity to task-specific constraints.

An alternative framework to interpret aspects of the present results is Logan's (1990) instance theory. According to this theory, processing on a given trial is due to a race between the direct retrieval of specific instances that reflect consistent interpretations of a stimulus within a given context, and more algorithmic on-line operations that involve the computations necessary to make the response. The notion is that with repetition, there is an increased likelihood of relying on direct retrieval, as compared to the more algorithmic on-line processing. Because algorithmic processes are more attention demanding, these processes might be slower, and hence reflect response latencies in the tail of the distribution. Within the ex-Gaussian framework, repetition would benefit those items that are more likely to go

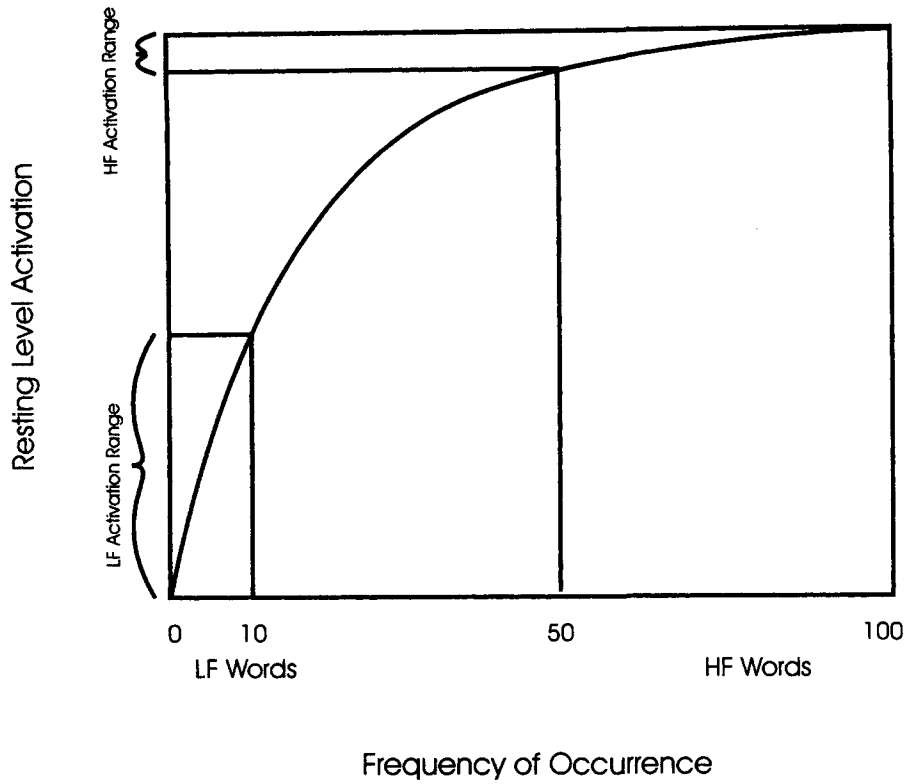

Figure 6. Hypothetical function relating observed frequency of occurrence of a word to the underlying resting level activations for the corresponding word recognition devices. LF = low frequency; HF = high frequency.

through the algorithmic operation, the items in the tail of the distribution (the low-frequency words in the lexical decision task). Thus, one should find a Frequency × Repetition interaction primarily in Tau, as the present results indicated. Although the instance-based model appears to accommodate aspects of the influence of repetition on the Tau component, this framework might have some difficulty accounting for observation that (a) frequency and repetition effects appear to involve different parameters for the same set of stimuli in lexical decision and naming, and (b) more importantly, the inhibitory influence of repetition for nonwords which is localized in Tau. Regarding the second observation, Logan (1990) observed facilitatory effects of repetition for nonwords in the lexical decision task, which is obviously in direct contrast to the present inhibitory effects of repetition. It is most likely the case that differences in the methods used across these studies might account for the different effects of repetition for nonwords. Logan investigated multiple repetitions over relatively short lags, whereas in the present study there was only a single repetition over relatively long lags (on average 20 min, and more than 150 intervening items). There is evidence that repetition effects may be quite distinct in these two different situations. Specifically, Ratcliff, Hockley, and McKoon (1985) have provided evidence for a distinction between relatively short-lived repetition effects (most likely measured in Logan's study) and the more long-term repetition effects (most likely measured in the present study).

Ratcliff's (1978) memory retrieval model also makes some clear predictions regarding the manner in which reaction time distributions might change (along with error rates) as a function of the present manipulations. This model has been explicitly used to generate reaction time distributions, and has been tested within an ex-Gaussian framework. Although the model was developed to explore episodic memory performance, it also nicely extends to other binary tasks such as lexical decision performance. The model assumes that during a reaction time trial, information accumulates until sufficient information has accrued to surpass some response threshold. The consistency of information accrual over time in support of a given response reflects a parameter called the drift rate in the model. Interestingly, changes in drift rate change both Mu and Tau. With respect to the present study, one might expect the drift rate to be lower for low-frequency words than for high-frequency words, thereby changing both Mu and Tau, as the present data indicated. As the drift rate decreases, one also finds a greater increase in Tau than in Mu. Thus, because the drift rate would already be lower for low-frequency words than for high-frequency words, one might expect repetition (which might be modeled by a change in drift rate) to influence Tau more for low-frequency words than for high-frequency words. However, the model may have some difficulty accommodating dissociations between Mu and Tau, as observed in the present data. That is, the model typically predicts that both Mu and Tau will be changed as

one modulates the drift rate. Thus, it is precisely these dissociations that may be particularly informative regarding the diffusion model (see also Balota, Cortese, Watson, & Spieler, 1998, for further dissociations).

Mapping Different Processes Onto Mu and Tau

We have taken a very simplistic view of the processes underlying Mu and Tau. This interpretation was motivated to some degree by the original arguments of Hohle (1965) who suggested that the influences of a variable on Mu are more likely to reflect processes related to both perception and response execution, whereas the influences of a variable on Tau are more likely to reflect central decision making processes. Although we believe that it is unlikely that such a mapping of parameter estimates (Tau vs. Mu) to underlying classes of processes (central–attentional vs. peripheral–automatic) will hold across different types of chronometric paradigms, it is worth mentioning two further pieces of evidence regarding this notion here. First, there is evidence from a series of attentional selection tasks that the influence of distracting information may differentially influence the Tau component depending upon the nature of the selection process. Specifically, as noted before, there is evidence that the interference effect in Stroop performance occurs in both Mu and in Tau. In the Stroop task both the color and word dimensions overlap within the same stimulus and so it is possible that this may involve relatively central decoupling operations of the critical word and color dimensions. However, attentional selection tasks that may be accomplished on the basis of relatively earlier level visual codes such as the spatial position (in the Flanker task) or the size of the selected stimulus (in the local–global task) appear to primarily produce a shift in the distribution (see Spieler, Balota, & Faust, 1995). Interestingly, Spieler (1997) has recently demonstrated that when one separates the color and word conditions within a spatial Stroop paradigm one can eliminate the interference effect that is found in Tau in the standard Stroop task. Spieler argued that in the spatial Stroop task, one can use an earlier spatial code to modulate the interference effect, thereby minimizing the influence on Tau.

The second finding that is at least supportive of our interpretation of the difference between the processes underlying Tau and Mu is the observation that older adults show larger effects in the Tau component in both Stroop and Lexical Decision than in the Mu component. Specifically, Balota, Spieler, and Faust (1994) reported evidence that the age-related increase in the size of the lexicality effect, the word-frequency effect, and the Stroop interference effect in mean response latencies are completely produced by an increase in the Tau component. In this light, it is interesting to note that Hasher and Zacks (1979) have argued that older adults produce relatively more of a breakdown in the attention demanding components of a task than the more automatic components (also see Balota, Black, & Cheney, 1992). Of course, given the present arguments regarding the nature of the decision process in the lexical decision task, and the above described description of the standard Stroop task, one might clearly expect an age-related change in both of these tasks primarily in the Tau component of the reaction time distribution. Finally, it is important to note that Spieler et al. (1995) also demonstrated that there is no disproportionate age-related increase in the Tau component in the attentional selection tasks that appear to be made on the bases of earlier spatial operations, such as local–global and Flanker tasks reviewed above.

Although it is tempting to map parameter estimates onto different classes of cognitive operations, again a word of caution is in order here. We believe that this mapping is useful only when one has a model of a targeted task and can specify how the processes might modulate the parameters of the reaction time distribution. It is clearly the case that depending upon both the task and the stimuli used in a given study that one might find a different mapping of types of cognitive operations onto distribution parameters. The important point to note is that the separation of Mu and Tau in the effects of variables provides important constraints for the types of models and processes that potentially produce such effects.

Rhyme Decisions and Lexicality

Although the present discussion has emphasized the lexical decision results, the results from the rhyme decision task also yielded a number of interesting patterns. First, as discussed above, the rhyme task did not yield any evidence of a word-frequency effect for the same set of words that produced relatively large word-frequency effects in lexical decision and naming performance. The lack of a word-frequency effect for this set of items is consistent with the notion that the presence of nonwords in the rhyme task increased the reliance on a frequency-independent sublexical code. Second, the results of the distribution analyses yielded a clear dissociation between the influence of factors on the means and the components of the RT distributions. Specifically, the results of the analyses of the means yielded highly reliable effects of decision (rhyming pairs produced a 50-ms benefit over nonrhyming pairs) and effects of lexicality (words produced a 30-ms benefit over nonwords). However, there was a complete dissociation concerning *where* the effects were occurring in the RT distributions. The response effect (i.e., rhyme pairs vs. nonrhyme pairs) was produced totally in a shift of the RT distribution, as reflected in changes in the Mu component, whereas the lexicality effect was produced totally in a stretching of the tail of the distribution, as reflected in changes in the Tau component. Although an account of this dissociation in rhyme decisions is premature at the present point, the important point to note here is that one would not have even observed the dissociation from estimates of central tendency.

Concluding Remarks

There are a number of different theoretical functions that one might use to fit an empirical RT distribution. Although Luce (1986) explores many such functions, he notes that the ex-Gaussian is one of the better functions to fit an empirical RT distribution. Why do we endorse the use of the ex-Gaussian? We believe there are three major advantages of

the ex-Gaussian: (a) The mean of a condition can be relatively well estimated by the simple sum of Mu and Tau, and therefore, the nature of previous effects that have been primarily obtained with measures of central tendency can be further understood by means of the decoupling of the parameters from the ex-Gaussian framework; (b) The exponential and the Gaussian components nicely parallel descriptive aspects of RT distributions (i.e., a central tendency component), and an estimate of skewing that may help in the communication across researchers in the field; and (c) the results of the present analyses, along with an accumulating set of studies (e.g., Balota, Spieler, & Faust, 1994; Gordon & Carson, 1990; Heathcote et al., 1991; Hockley, 1984; Ratcliff, 1979; Spieler et al., 1995), indicate that the characteristics of the ex-Gaussian are relatively stable across participants. Although there is the risk of using the incorrect description of RT distributions, we do believe that at the present point in theory development, it is worthwhile to consider the ex-Gaussian as a useful way of describing the influence of a factor on different components of RT distributions. As noted in the *Introduction*, there have been a number of important demonstrations of the utility of this approach in theory development (e.g., Mewhort et al., 1992; Ratcliff, 1978, 1979; Wixted & Rohrer, 1993). Thus, at this level, the present study is simply an addition to the growing list of studies employing this approach. Whatever one chooses as the estimate of an effect of a condition on the characteristics of the RT distribution, we believe that it is time to go beyond simple estimates of central tendency in the study of mental chronometry.

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