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A diffusion model account of normal and impaired readers

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Abstract

Acquired aphasics and dyslexics with even very profound word reading impairments have been shown to perform relatively well on the lexical decision task (e.g., Buchanan, Hildebrandt, & MacKinnon, 1999), but direct contrasts with unimpaired participant's data is often complicated by extremely long reaction times for patient data. The dissociation between lexical decision and word naming performance shown by these patients is of theoretical importance, and here we present an analysis of processing underlying the lexical decision task. We are able to determine what aspects of performance are affected by acquired aphasics in the lexical decision task. We fit lexical decision data from aphasic patients and from normal readers with a sequential sampling model (the diffusion model; Ratcliff, 1978; Ratcliff, Van Zandt, & McKoon, 1999) that simultaneously considers reaction time and accuracy. This model provides a powerful means of assessing processes involved in impaired and unimpaired lexical decision. Our results suggest that lexical decision may tap impairments at both a linguistic and a nonlinguistic level. These impairments combine to make patients produce the exaggerated lexical decision reaction times typical of neurolinguistic patients: we demonstrate that patients have compromised decision and nondecision processes but that the quality of the information upon which they base their decisions is not much different from that of unimpaired participants.

1. Introduction

Mean correct response time (RT) and accuracy are two ubiquitous dependent variables in many two-choice tasks (e.g., lexical decision, semantic categorization, recognition memory, among many others). In the typical experiment with a normal population, error rates are often low and usually ignored and the RT data is taken as primary. However, this (previously standard) way of analyzing the data ignores valuable information such as error RTs, the shape of the RT distribution for correct and error responses, and accuracy (see Ratcliff & Murdock, 1976). Moreover, an effect of variables on speed and accuracy, or sometimes the presence of an effect in the error rates but not in the mean correct RTs, can complicate the interpretation of the results.

When we deal with data from special populations (e.g., patients with brain damage), we face additional problems. Even though acquired aphasics and dyslexics with even very profound word reading impairments have been shown to perform relatively well on tasks such as lexical decision task (i.e., word/nonword discrimination task; see Buchanan, Hildebrandt, & MacKinnon, 1999), both the variability in the RTs and the error rates tend to be substantially larger than with normal populations (e.g., see Moreno, Buchanan, & Van Orden, 2002). Under these circumstances, it has been argued that analyses based on the mean RT per condition may produce unstable estimates (Moreno et al., 2002). For instance, Moreno et al. failed to find a significant word-frequency effect in the RT analyses (i.e., faster responding for higher than for lower frequency words) in three out of nine impaired readers. Indeed, as Moreno et al. (2002) noted, variability in RTs often differs across conditions, which implies that trimming procedures may spuriously affect one condition more than others (e.g., a 2000 ms cutoff may affect low-frequency words more than high-frequency words; see also Ratcliff, 1993). For that reason, it has been suggested

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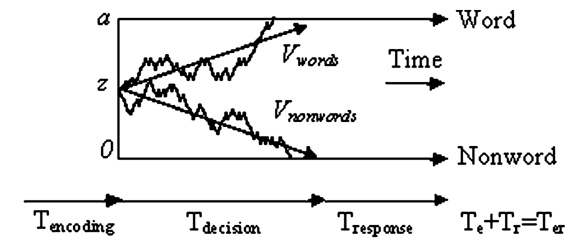
that a measure of sensitivity such as d' (i.e., the difference in the z transformed hit rate minus the z transformed false alarm rate) should be the measure of choice as opposed to mean RT when studying data from special populations (e.g., Moreno et al., 2002). In the context of the lexical decision task, d' can be computed as the z score of the proportion of correct responses to word trials (i.e., hit rate) minus the z score of the proportion of words responses to nonword trials (i.e., false alarms). The problem is that using d' alone means that RT data is ignored, and even though it is variable, it can convey valuable information. As noted above, researchers usually ignore the error RTs and the shape of the RT distributions in the data from normal populations. In the case of special populations, the exclusive use of d' would imply that *all* RT data would be ignored.

A complementary strategy for examining data in two-choice tasks is to use a model that *simultaneously* accounts for speed and accuracy data. A sequential-sampling model such as the diffusion model (Ratcliff, 1978) provides such an account. A large body of data has shown that the diffusion model provides an adequate account for two-choice RT tasks in terms of both correct and error RTs and their relative speeds, the shape of the RT distributions for both correct and error responses, and response probabilities values (e.g., Ratcliff, 1978, 1988; Ratcliff, Gómez, & McKoon, 2004; Ratcliff & Rouder, 1998; Ratcliff, Thapar, & McKoon, 2001; Ratcliff, Thapar, & McKoon, 2003; Ratcliff, Van Zandt, & McKoon, 1999). Furthermore, the diffusion model allows RT data to be examined in terms of the components of processing required by a cognitive task. This allows comparisons between data from the young adult population and other populations, such as older adults (see Ratcliff et al., 2001, 2003; Thapar, Ratcliff, & McKoon, 2003). This comparison has provided valuable interpretations of the effects of aging on the cognitive components. In general, older adults show more conservative decision criteria and a slower nondecision component than the younger adults, whereas the differences in the rate of accumulation evidence are, in many cases, small or null (Ratcliff et al., 2001, 2003).

We believe that it is important to examine whether a comprehensive quantitative model such as the diffusion model can account for data from subjects of special populations such as impaired readers. If it can, the diffusion model may provide insights about the components of processing that differ between impaired and unimpaired participants (i.e., in terms of the rate of accumulation of evidence, drift rate, the amount of evidence required for a decision, decision criteria, or components of processing other than the decision process). To that end, here we present fits of the diffusion model to data from the lexical decision task with impaired and normal readers. But before we examine the fits of the model, it is necessary to briefly describe the diffusion model.

The diffusion model is a model for a single-stage decision process (i.e., mean RTs should be not much longer than 1 or 1.5 s) that assumes that decisions are made by a noisy process that accumulates noisy information over time from a starting point toward one of two response criteria or boundaries ("word" and "nonword" boundaries in the lexical decision task; see Fig. 1), where the starting point is labelled z and the boundaries are labelled a and 0. When one of the boundaries is reached, a response is initiated. Speed–accuracy tradeoffs occur when the boundaries change their distance from the starting point. Boundaries far from the starting point produce slow and accurate responses, while boundaries close to the starting point produce fast and inaccurate responses. The rate of accumulation of information is called the drift rate (v), and it is determined by the quality of the information extracted from the stimulus. For example, if a familiar word (e.g., *TABLE*) were displayed in a lexical decision task, information quality would be good and the mean value of the drift rate toward the a boundary would be large (see Ratcliff et al., 2004). Another important parameter in the model corresponds to the components of processing that are not included in the decision process (T_{er}, i.e., processes such as stimulus encoding, lexical processing prior to evidence being output to the decision process, and response execution). The diffusion model assumes that there is variability in the above described parameters. A detailed description of the variability parameters in the model would be beyond the scope of the present study (see Ratcliff et al., 1999; Ratcliff & Tuerlinckx, 2002). But what should be noted is that within each trial, there is noise (i.e., variability) in the process of accumulating information so that processes with the same mean drift rate do not always terminate at the same time (producing RT distributions) and do not always terminate at the same boundary (producing errors). Fig. 1 shows a diffusion process with the mean drift rate represented by the arrow and the accumulation of noisy information represented by the jagged line. Within-trial variability in drift rate, s, is a scaling parameter for the diffusion process (i.e., if it were doubled, other parameters could be multiplied or divided by two to produce exactly the same fits of the model to data). In addition, between-trial variability, η, is assumed so that stimuli of the same nominal category (e.g., high-frequency words) may have different drift rates in different trials: this is analogous to variability in signal and noise strength in signal detection theory. Finally, the model also assumes variability in starting point, s_z (e.g., a high degree of variability in starting point leads to fast errors; see Ratcliff & Rouder, 1998), and in the nondecision component, s_t (see Ratcliff et al., 2004; Ratcliff & Tuerlinckx, 2002).

To examine the fits of the model to empirical data from impaired readers, we used data from the lexical



Parameters:

a Boundary separation
z Starting point
v Drift rate (one per each type of stimulus)
T_{er} Mean of the nondecision components of processing (e.g., encoding and response output processes)

Parameters for fits of the diffusion model in the experiments

	a	T_{er}	η	s_z	Drift rates (v) HF W	LF W	NW	s_t	z	chi-square
impaired readers										
super-subj A	0.283	0.577	0.098	0.169	0.262	0.167	−0.190	0.350	0.115	92.1
super-subj B	0.233	0.594	0.049	0.095	0.181	0.077	−0.121	0.335	0.117	118.0
super-subj C	0.393	0.815	0.049	0.004	0.072	0.029	−0.062	0.001	0.182	45.6
unimpaired readers										
super-subj D	0.147	0.470	0.139	0.023	0.409	0.218	−0.276	0.140	0.062	110.4
super-subj E	0.148	0.459	0.128	0.030	0.323	0.161	−0.188	0.158	0.070	322.4
super-subj F	0.196	0.481	0.111	0.060	0.285	0.161	−0.200	0.163	0.088	127.4

	a	T_{er}	η	s_z	Drift rates (v) Words	Random	NW	Pseuhom	s_t	z	chi-square
JO	0.237	0.942	0.098	0.004	0.203	−0.273	−0.149	−0.133	0.350	0.097	157.3

Fig. 1. An illustration of the diffusion model (top panel; the jagged line illustrates a sample path with drift rate equal to the arrow) and associated parameter values for fits of the diffusion model (bottom panel).

decision experiment of Moreno et al. (2002). Nine right-handed subjects with brain damage in the left hemisphere performed a lexical decision experiment, with 74 high-frequency words, 74 low-frequency words, and 148 nonwords. The patients were selected for inclusion in the Moreno et al. study on the basis of having language disorders that showed up as atypical error rates on a word reading task that consisted of 300 common monosyllabic words. The range of impairment varied greatly with some patients making less than 10% errors on the reading task to others making nearly 90% errors. Eight out of the nine patients had brain damage that was caused by a vascular incident; whereas the ninth patient (JO) had brain damage as a consequence of treatment for a tumour.

The goal of the present study is not just to examine the fits of the diffusion model to the data from patients with brain damage, but also to examine whether there are any systematic differences in the components of processing in the diffusion model for normal and impaired readers (e.g., in terms of the speed of the accumulation process and/or in terms of the decision boundaries). Consequently, for comparison purposes, we also examined the fits of the diffusion model to empirical data from normal readers. To that end, we used the lexical decision data from the parallel experiment with 39 college students as controls. The materials and instructions were the same for the patients and the normal subjects (i.e., patients and controls were asked to respond as quickly as possible the "word" or "nonword" keys while remaining accurate). Each subject received the items (words or nonwords) in a random sequence.

2. Fits from the diffusion model

To examine correct and error RT distributions, we used the RTs of each participant to estimate five quantile RTs: the .1, .3, .5, .7, and .9 quantiles. However, in order to obtain five quantiles RTs, each condition must contain at least five responses. Given the low error rate for high-frequency words, we did not have enough responses to obtain the quantiles for error responses for a number of subjects. For that reason, we opted to conduct two potentially converging procedures. The first procedure was to create a small number of "super-subjects" by combining the data from subjects that behaved similarly (see below) so that there were at least five data points per correct and error condition. We then performed fits of the model to these super-subjects. The second approach was to use the individual subjects. Because the number of error RTs in some cases was below five (especially for the high-frequency words), we made the assumption that the error RTs for those conditions behaved similarly to the error RTs to the conditions in which we had enough error responses. Specifically, the quantiles for the error RTs computed as a linear combination of the corresponding quantiles for the error RTs to low-frequency (LF) words and the correct RTs to high-frequency (HF) words. We then compared the parameter values obtained for the two methods and found that the average parameter values from the super-subject analysis were close to the median parameter values for the single subject analysis, which means that the two methods produced very similar results.

For the set of patients, we created three "super-subjects" by grouping the data from participants in a decreasing order of performance. Super-subject A was composed of participants with good performance for both high- and low-frequency words (super-subject A: BC, BV, and LA; probability correct: .99, .93, and .91 for HF-words, LF-words, and nonwords; and correct mean RTs: 1052, 1221, and 1413 ms for high-frequency words, low-frequency words, and nonwords). Super-subject B was composed of participants with somewhat poorer performance with unfamiliar words (super-subject B: JM, JO, MH, and WM; probability correct: .97, .78, and .93 for HF-words, LF-words, and nonwords; mean correct RTs: 1208, 1459, and 1450 ms for high-frequency words, low-frequency words, and nonwords). Finally, super-subject C was composed of the two participants with dramatically high response times–over 2700 ms for high-frequency words—(super-subject C: MD and RB; probability correct: .87, .69, and .82 for HF-words, LF-words, and nonwords; and mean correct RTs: 2914, 3247, and 3512 ms for high-frequency words, low-frequency words, and nonwords). By using an analogous criterion, we also created three super-subjects out of 39 normal readers (super-subjects D, E, and F). Specifically, for super-subject D, the probability correct was .98, .90, and .94 for HF-words, LF-words, and nonwords; mean correct RTs: 644, 716, and 805 ms for high-frequency words, low-frequency words, and nonwords. For super-subject E, the probability correct was .95, .81, and .92 for HF-words, LF-words, and nonwords; mean correct RTs: 665, 772, and 894 ms for high-frequency words. For super-subject F, the probability correct was .97, .88, and .94 for HF-words, LF-words, and nonwords; mean correct RTs: 842, 985, and 1088 ms for HF-words, LF-words, and nonwords.

To fit the diffusion model to the super-subjects data, we formed a χ^2 statistic (see Ratcliff & Tuerlinckx, 2002) and this value was minimized by adjusting the parameter values using a general SIMPLEX minimization routine (Nelder & Mead, 1965). The data that were entered into the minimization routine for each experimental condition were the five quantile RTs for each super-subject for both correct and error responses and the associated accuracy values. The quantile RTs were fed into the diffusion model and, for each quantile, the cumulative probability of a response by that point in time was generated from the model. Subtracting the cumulative probabilities for each successive quantile from the next higher quantile yields the proportion of responses between each quantile. For the χ^2 computation, these are the expected values, which are to be compared to the observed proportions of responses between the empirical quantiles. The expected values were multiplied by the number of observations to produce expected frequencies. The observed proportions of responses for the quantiles are the proportions of the distribution between successive quantiles (i.e., the proportions between the 0, .1, .3, .5, .7, .9, and 1.0 quantiles are .1, .2, .2, .2, .2, and .1) multiplied by the probability correct for correct response distributions or the probability of error for error response distributions (multiplied by a number proportional to the number of observations in the condition). Summing over (Observed − Expected)^2/Expected for correct and error responses for each type of word and nonword gives a single χ^2 value to be minimized:

$$\chi^2 = \sum (O - E)^2 / E.$$

Fig. 2 shows the results for the experiment. Panels A–C show the data and fits of the diffusion model for the impaired readers, and Panels D–E shows the data and fits from the normal readers. On the y axis is plotted the 5 quantile RTs (white circles) in a vertical row for each condition (HF words, LF words, and nonwords) for correct and error responses. The black circles represent the fits of the models. The response probabilities per each condition appear at the top of the corresponding quantiles and the values between brackets represent the predicted responses probabilities. The starting point (or leading edge) of the RT distributions is represented by the .1 quantile (i.e., the circles at the bottom of each column) and the skew is represented by the spread of the higher quantiles. The fits to the response probabilities are excellent, for both the impaired and the unimpaired

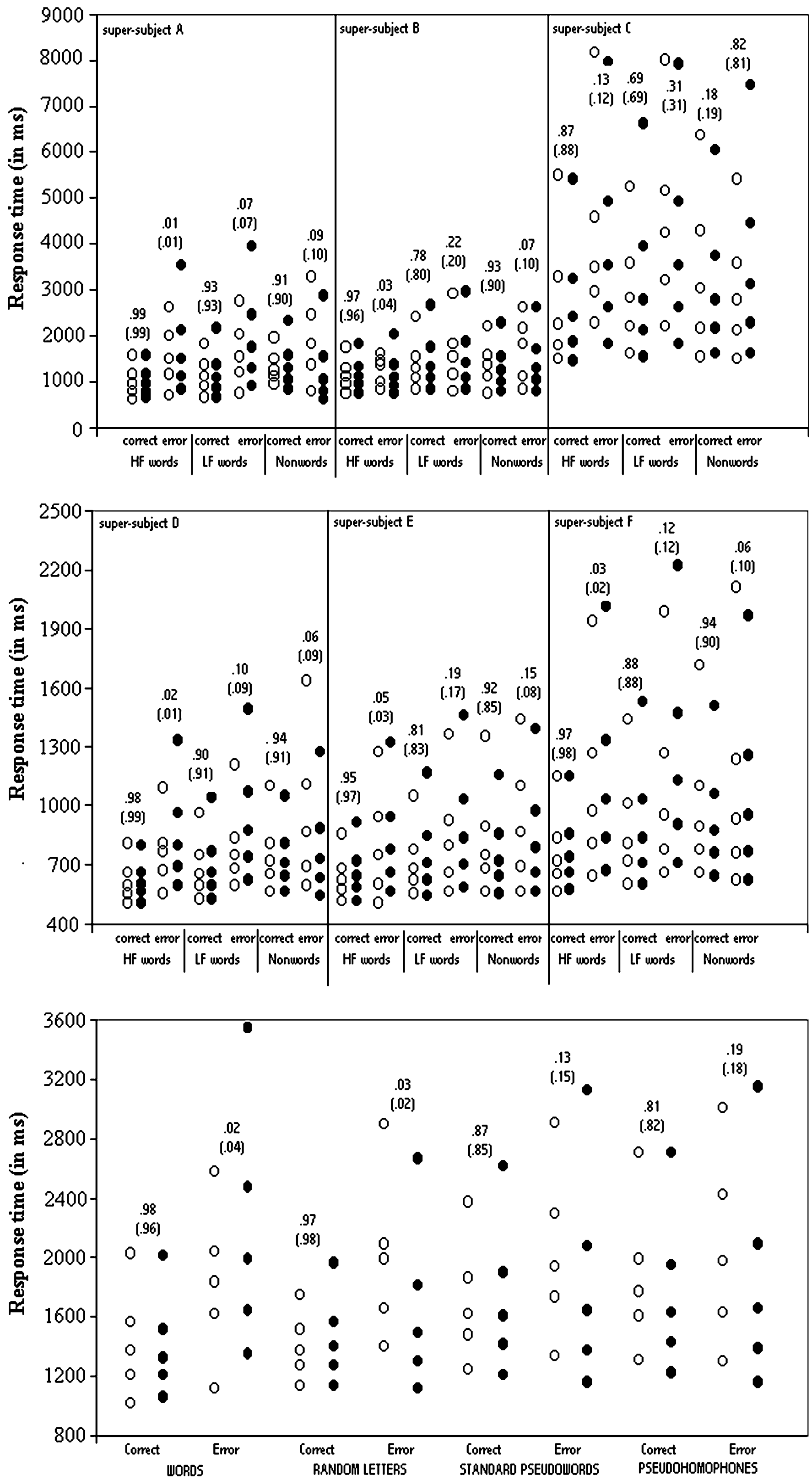


Fig. 2. Data and model fits for the experiments. The top panels (Panels A–C and Panels D–F) show data from the impaired and the control readers, respectively. The bottom panel shows data from a patient (JO) in a second experiment. The columns represent the responses for the different stimulus types. The white circles in the figure represent the quantiles of the empirical RT distributions (i.e., the first circle from bottom to top represents the .1 quantile, the second circle the .3 quantile, and so on). The black circles represent the fits of the diffusion model. The observed response probabilities per stimulus type appear at the top of the corresponding quantiles (the values between brackets represent the predicted responses probabilities).

participants (see Fig. 2). As usual, the RT distributions were positively skewed (i.e., there is a larger separation between the higher quantiles than between the lower quantiles), which is the usual finding in RT studies. This feature is easily captured by the geometry of the diffusion model (Ratcliff, 1978; Ratcliff et al., 2004). The fits to the RT distribution (i.e., the difference between the white and black circles) are very good, despite the fact that the latencies for the impaired readers are quite high. It is worth noting that correct RTs appear to be fit much better than errors (see Fig. 2); but the quality of the fits is similar because error RTs are more variable (see Ratcliff & Tuerlinckx, 2002).

The parameter values from the diffusion model for the six super-subjects (three from the patients and three from the normal subjects) are given in Fig. 1. Results show some differences as well as some similarities between impaired and unimpaired participants. Impaired participants clearly set more conservative decision criteria than unimpaired (i.e., they set the response boundaries farther apart, which correspond to higher values of the a parameter). In other words, impaired participants seem to require more information to reach a decision than unimpaired participants. Likewise, the nondecision component (i.e., encoding processes, lexical access processes, and response execution processes) is also substantially higher (100 ms or more) for the impaired than for the unimpaired participants. In contrast, when we examine the rate of accumulation of information (drift rate parameters), the differences between impaired participants (at least for those in groups A and B) and unimpaired participants are rather small. This means that the quality of information entering the decision process in the lexical decision task is not much different for the groups (except in the case of super-subject C). The present analyses also confirm that high-frequency words produce larger drift rates than low-frequency words in the lexical decision task: in other words high-frequency words are more word-like in a "wordness" dimension than the low-frequency words (see Ratcliff et al., 2004); this frequency effect clearly holds for both impaired and unimpaired participants, including super-subject C. Bear in mind that we use the term "wordness" as a theoretically neutral term that serves as a meeting point between the diffusion decision model that works back from the data to estimate the quality of evidence driving the decision process and models of lexical processing and structure that would provide an output that would map into "wordness."

As stated above, we also performed fits of the diffusion model to the empirical data on a subject-by-subject basis rather than by using super-subjects. The general procedure was analogous to that used with the super-subjects. In Fig. 3, we present the box plots for the most relevant variables for our purposes [boundary separation, nondecision processes, the drift rates for high-frequency words, low-frequency words, nonwords, and the combined (average) drift rate of the three stimulus types]

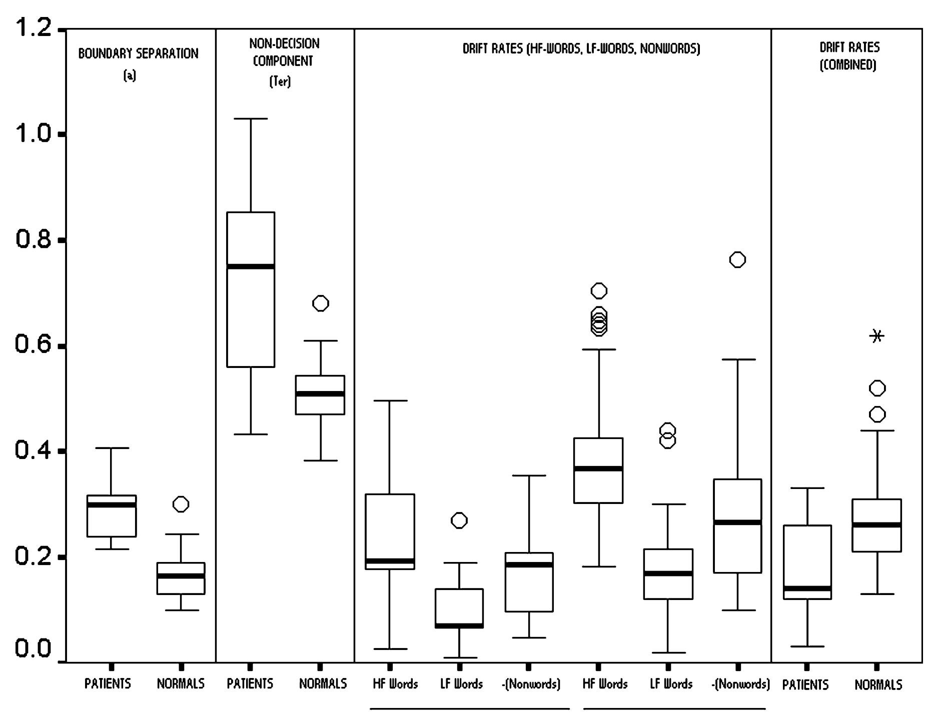


Fig. 3. Box plot with the distributions, across patients and controls, of the boundary separation parameter (a), the nondecision component (T_{er}), the drift rates for high-frequency words, low-frequency words, nonwords (in absolute value), and the combined (average) drift rate value across the three stimulus types. The "X" signs represent the average value of the above indicated parameters from the diffusion model for the super-subjects.

on the patients and the normal subjects. The behaviour of the parameter values derived from fits to individual subjects were very close to those from the analyses based on super-subjects: the means of the parameters obtained by using super-subjects lie within the bulk of the distributions for the individual subjects and are close to the median parameter values (see Fig. 3; the "X" signs in Fig. 3 represent the average value of the parameters from the diffusion model for the super-subjects and the middle line in the box represents the median parameter values from individual subjects).

There is very little overlap in the distributions on boundary separation for the patients and the control subjects: impaired readers tend to use more conservative criteria to make their lexical decision responses ($F(1,46) = 48.40$, $p < .001$, $\eta^2 = .51$). In addition, the nondecision component is substantially larger for the patients than for the controls ($F(1,46) = 37.17, p < .001$, $\eta^2 = .45$). Drift rates, as measured by the combined drift rate, are lower for the patients than for the controls but, as can be seen in Fig. 3, there is some overlap between the distributions ($F(1,46) = 6.84$, $p < .015$, $\eta^2 = .12$) and the differences in effect size (as measured by η^2) between the impaired and the unimpaired participants is substantially smaller than with the boundary separation or the nondecision components. Finally, it is worth noting that *all* nine impaired readers showed a substantial word-frequency effect in the parameter corresponding to quality of information (i.e., higher drift rates for high-frequency words than for low-frequency words; BC: .32 vs .19; BV: .46 vs .27; LA .19 vs .11; JM .19 vs .07; JO .20 vs .07; MH .18 vs .04; NM .49 vs .14; MD .16 vs .07; RB .03 vs .01). (Likewise, all control subjects showed an advantage in terms of drift rates for high-frequency words compared with low-frequency words.)

Although the present lexical decision results are straightforward and show converging evidence with the two procedures, it may be important to show the fits of the diffusion model in a situation in which we do not have to use super-subjects or make any assumptions regarding the distributions of the error RTs. For that reason, we present lexical decision data from an additional experiment with a large number of observations on one of the above-described patients (JO). The data reported here are from a larger unpublished study investigating word naming and lexical decision performance with JO, a deep dyslexic patient who is described elsewhere (Buchanan, McEwen, Westbury, & Libben, 2003). Specifically, JO was presented (over four testing sessions) with 2396 items: 1200 words and 1196 nonwords (these nonwords were either random consonant letters, 276, e.g., m*crgk*; standard nonwords, 632, e.g., c*oant*; or pseudohomophones, 288, e.g., *grane*; note that *grane* is pronounced like the word *grain*). We had more than five error RTs in all conditions, despite the fact that error rates were quite low (e.g., 2% for words or 3% for random letters). (Note that JO read aloud the same set of words for which she performed the lexical decision and she read less than half of the items correctly; Colangelo, Buchanan, & Westbury, in press.) Given that lexical decisions are posited to be driven by a "wordness" dimension in the diffusion model (Ratcliff et al., 2004), the model predicts larger negative drift rates for the least word-like strings (i.e., random consonants), intermediate values for the standard nonwords, and small negative values of drift rate for the most wordlike strings (i.e., pseudohomophones). (In other words, random letter strings are predicted to be classified as "nonwords" faster than the standard nonwords, and the standard nonwords are predicted to be classified as "nonwords" faster than the pseudohomophones.)

The general procedure for fitting the diffusion model to the empirical data was the same as that used in the previous analyses. The parameter values from the diffusion model for JO are given in Fig. 1 and the bottom panel of Fig. 2 shows the results and fits for the experiment. As expected, the drift rates for random consonant strings are lower than the drift rates for the standard nonwords (−0.27 vs −0.15), and in turn, the drift rates for the standard nonwords are lower than the drift rates for the pseudohomophones (−0.15 vs −0.13). It is worth noting the extremely high value of the nondecision component (942 ms); this is not surprising given the high latencies even when classifying the random consonant letters as "nonwords" (i.e., the .1 quantile was over 1 s). The value of the boundary separation was also rather high (and similar to the values for the other impaired readers; see Fig. 1). As in the previous experiment, 5 quantile RTs are plotted on the *y*-axis (white circles) in a vertical row for each condition (words, random letters, standard nonwords, and pseudohomophones) for correct and error responses. The black circles represent the fits of the model. The response probabilities per each condition appear at the top of the corresponding quantiles and the values between brackets represent the predicted responses probabilities. The fits to the response probabilities are excellent (i.e., the difference between the predicted and the observed probabilities is always less or equal than .02) and the fits to the RT distributions are reasonable good given the fact that the RTs were quite high. (Only in the RT distributions with a low error rate does the model miss the shape of the distributions; this is caused in part by the small number of observed data points.) Finally, as predicted, the model captures the differences in drift rate between the random consonant strings, the standard nonwords, and the pseudohomophones in terms of a "wordness" dimension (i.e., highest drift rates for pseudohomophones and lowest drift rates for nonword-like consonant strings).

Differences in drift rate for the consonant strings vs the nonpseudohomophonic nonwords indicate that patients are sensitive to the orthographic characteristics of the nonwords. Such an effect is not surprising, nor is it of particular theoretical interest. However, the drift rate differences between pseudohomophones and the standard nonwords is of theoretical interest given that numerous early models of deep dyslexia posited a failure in sublexical processing of phonological information (see Plaut & Shallice, 1993, for discussion). If this failure were indeed responsible for the symptoms associated with deep dyslexia then the above differences between pseudohomophones and standard nonwords would be unexpected because these items differ only with respect to their phonological overlap with real words. The results from this analysis therefore lend support to the contention that deep dyslexics are sensitive to nonword phonology despite their failure to read such items aloud (e.g., Buchanan et al., 1999).

The present study, therefore, illustrates that the diffusion model can be successfully applied to data from impaired readers. Despite that the RTs with patients are quite high (e.g., in some cases over 2700 ms, see above), the model provides reasonably good fits in terms of accuracy, speed, and the shape of the RT distributions for correct and error responses. Furthermore, the analysis of lexical decision data of JO, with more than 2000 trials, also shows good fits at the individual level, despite the presence of the extremely high decision times. More important, by using the diffusion model to examine the data, we have shown that it is both the decision criteria and the nondecision components (i.e., encoding processes, lexical processes that are not part of the decision process, and response execution) rather than the differences in the quality of information (*drift rate* in the diffusion model) that produces the difference in performance between impaired and unimpaired participants. In other words, besides setting a more conservative criterion to make their lexical decision responses, the duration of the nondecision components (which includes lexical access processes) seem to take longer for the impaired than for the normal subjects, albeit at the end they get nearly the same information (i.e., drift rates) for the word/nonword decision process as the normal readers. This pattern of results is consistent with the view that aphasic patients suffer from a failure of inhibition that leads to difficulties with lexical selection as opposed to damage to the lexical representations themselves (Buchanan et al., 2003).

Thus, the take-home message is that when analyzing data from normal and special populations, it is essential to focus on the data as a whole. This approach has been employed successfully in a number of experiments comparing the performance of young and old adults in different two-choice decision tasks (e.g., Ratcliff et al., 2001, 2003). Similar to the present study, many of the changes between the young and the old adult population are in the boundary separation and in the nondecision component rather than in the quality of information that enters the decision process. This observation gives rise to two separate but intriguing lines of inquiry. First, it may be worth studying whether the differences between the impaired and unimpaired readers also appear when the task does *not* tap a language component (e.g., shape discrimination). It may be that impaired readers simply use more conservative criteria before they make their responses independent of whether those responses tap purportedly damaged processes. From there it might be possible to use subtractive logic to isolate the differences in lexical processes alone. A second line of inquiry that is suggested by the current study is an extension that directly contrasts impaired participants with elderly participants to determine whether the caution found in our patients is similar to that demonstrated by elderly participants in similar studies. Such a comparison may provide important insight into the source(s) of cognitive slowing associated with aging.

In sum, a quantitative analysis in terms of the diffusion model provides valuable additional information relative to the components of processing beyond the mean RT, response probabilities, or any measure of sensitivity (d'). The application of such a model in cognitive neuropsychology studies promises to provide interesting insights into the ways in which brain damage can impair the componential processes required in a particular task.

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