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A Model of the Go/No-Go Task

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In this article, the first explicit, theory-based comparison of 2-choice and go/no-go variants of 3 experimental tasks is presented. Prior research has questioned whether the underlying core-information processing is different for the 2 variants of a task or whether they differ mostly in response demands. The authors examined 4 different diffusion models for the go/no-go variant of each task along with a standard diffusion model for the 2-choice variant (R. Ratcliff, 1978). The 2-choice and the go/no-go models were fit to data from 4 lexical decision experiments, 1 numerosity discrimination experiment, and 1 recognition memory experiment, each with 2-choice and go/no-go variants. The models that assumed an implicit decision criterion for no-go responses produced better fits than models that did not. The best model was one in which only response criteria and the nondecisional components of processing changed between the 2 variants, supporting the view that the core information on which decisions are based is not different between them.

Keywords: go/no-go, modeling, lexical decision task, recognition memory, perceptual decision making

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The primary task that has been used to assess performance in paradigms that measure response time (RT) is a two-choice procedure. In a typical experiment, a stimulus is presented and one of two choices is made, usually by pressing one of two response keys. A less common alternative is the go/no-go procedure, in which subjects are required to respond to one of the choices but must withhold a response to the other alternative (see Donders, 1868/1969). In comparing these tasks, it is puzzling that mean RTs are sometimes shorter and accuracy is higher for the go responses in the go/no-go task than for the corresponding responses in the two-choice task.

This difference in results has raised a question as to which procedure provides a better window into the processes of interest (e.g., lexical access, memory, perceptual discrimination). Two explanations have been proposed. First, different procedures might induce subjects to adopt different biases in the decision process in addition to there being differences in nondecisional processes. In this view, the processes induced by the go/no-go procedure versus the two-choice procedure differ only in ancillary components, without affecting the central components of the process of interest (e.g., Gordon, 1983; Hino & Lupker, 1998). Second, different procedures might change the core processes involved in the task (e.g., Gibbs & Van Orden, 1998; Grice & Reed, 1992; Perea, Rosa, & Gómez, 2002). To date, neither suggestion has been based on analysis that incorporates quantitative modeling. Although the equivalence of these procedures has received little attention, the issue has arisen recently in evaluating lexical processing, particularly in the lexical decision task.

The aim of the research presented here is to determine why results from experiments using the two-choice procedure differ from those using the go/no-go procedure. Our examination of the relationship between the two procedures is focused on the lexical decision task, on a numerosity discrimination task (Espinoza-Varas & Watson, 1994; Ratcliff, Van Zandt, & McKoon, 1999), and on recognition memory (Ratcliff, 1978; Ratcliff, Thapar, & McKoon, 2004), but the results and approach should apply to any domain that uses these two procedures. Much of the recent work on comparing the go/no-go and the two-choice procedures has focused on the lexical decision task. We present our initial discussion using this task and then later show that our findings generalize to numerosity discrimination and recognition memory.

The approach used here is to apply a quantitative model, the diffusion model (Ratcliff, 1978), to the two procedures, making different assumptions about how components of processing differ from one procedure to the other. The diffusion model is a model of the processes involved in relatively fast two-choice decisions involving a single-stage decision process (as opposed to the multiple-stage decision processes that might be involved in, for example, reasoning tasks). Similar models have also been applied to simple reaction time (Smith, 1995) and decision making (Buse-

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meyer & Townsend, 1993; Roe, Busemeyer, & Townsend, 2001). Recently, the diffusion model has successfully accounted for data from word recognition (lexical decision) experiments (Ratcliff, Gomez, & McKoon, 2004; Ratcliff, Thapar, Gomez, & McKoon, 2004). To date, the diffusion model has been used exclusively in the context of experiments that use the two-choice procedure.

The two-choice procedure and the go/no-go procedure use RT and accuracy as dependent variables. The two-choice task is the most widely used of all RT-based procedures within the field of cognitive psychology (e.g., Rubinstein, Garfield, & Millikan, 1970). Although the go/no-go procedure is not used as widely as the two-choice procedure, it has a long history too (Donders, 1868/1969; see Luce, 1986, for a review), and its use is increasing in several areas, for example, in bilingualism (Dijkstra, Timmermans, & Schriefers, 2000), neuropsychology (Goldberg et al., 2001), visual-word recognition (Hino & Lupker, 2000), masked priming (Mathey, Robert, & Zagar, 2004), speech production (Schiller, 2002), semantic categorization (Siakaluk, Buchanan, & Westbury, 2003), clinical visual-field testing (Lutz et al., 2001), object recognition (Tarr, Williams, Hayward, & Gauthier, 1998), and recognition memory (Boldini, Russo, & Avons, 2004). In addition, the go/no-go procedure has a long tradition in animal behavior research that includes some contemporary research on decoupling neural activity resulting from the stimulus from neural activity resulting from the decision to make a response (Basso & Wurtz, 1998; Sommer & Wurtz, 2001). In spite of the use of this procedure in many areas of research and in many theoretical debates, it has not been explicitly modeled; in this article we present a model of the go/no-go task and examine how it differs from the two-choice task.

Go/No-Go Versus Two-Choice Experiments: A Brief Review

The cause of the differing results with the two procedures was first discussed by Donders (1868/1969). Donders argued that the two-choice procedure merely included an additional process of response selection in addition to the decision of interest (e.g., the word vs. nonword decision in the lexical decision task). According to this view, RT for the two-choice procedure minus RT for the go/no-go procedure should yield an estimate of the duration of the response selection process.

Donders's subtractive method has been controversial since its inception. For example, Wundt (1880) pointed out that the go/no-go procedure may also require response selection because the subject must choose whether to respond or not (see also Cattell, 1886). Currently, very few researchers would agree with Donders's subtractive logic, and current explanations for the difference between procedures involve more sophisticated mechanisms (see Ulrich, Mattes, & Miller, 1999, for a review of Donders's assumption of pure insertion).

The go/no-go procedure was first applied to the lexical decision task by Gordon and Caramazza (1982; Gordon, 1983). Gordon and Caramazza claimed that the go/no-go procedure resulted in better performance and data that were less noisy than data from the two-choice procedure. For the lexical decision task, they acknowledged that the core processes responsible for a "word" response could differ across the two lexical decision procedures but stated that this was "unlikely on a priori grounds" (Gordon, 1983, p. 35). Instead, they argued that the use of the go/no-go procedure would make the mechanics of "response selection" simpler than the two-choice procedure and, hence, that it would "minimize response confusions and errors and reduce the variance of correct responses" (Gordon & Caramazza, 1982, p. 148). Gordon and Caramazza suggested that the two-choice task "may demand two decisions from the subject" (Gordon & Caramazza, 1982, p. 148; cf. Pachella, 1974): the lexical decision itself (word or nonword) and a response execution decision.

Chiarello, Nuding, and Pollock (1988) and Measso and Zaidel (1990) compared the go/no-go and the two-choice lexical decision tasks by examining not only the mean RTs but also signal detection measures (i.e., d', a criterion-free estimate of discriminability, and log β, a decision bias index). They found substantially shorter RTs for words in the go/no-go task, whereas the values of d' and β were similar in the two procedures. Measso and Zaidel (1990) also included a go/no-go procedure for "nonword" responses, in which subjects had to press a key only when the presented stimulus was a nonword; in this case, Measso and Zaidel failed to find any reliable RT differences between the go/no-go and the two-choice procedures.

Hino and Lupker (1998, 2000) found that the word-frequency effect (i.e., shorter RTs for high-frequency words than for low-frequency words) was larger in the go/no-go task than in the yes–no task, and they proposed that in the two-choice procedure, there is pressure to make a rapid response to all stimuli (words and nonwords). Accordingly, when an unfamiliar low-frequency word is encountered, subjects may make a "nonword" response, and these trials end up counting as errors but not contributing to the mean correct latency for low-frequency words. In contrast, nonwords do not require a response in the go/no-go procedure. Thus, when an unfamiliar word is encountered, a "nonword" response cannot be made, and lexical processing continues. In this case, the subject may make a slow response (assuming that the word is in the individual's vocabulary), which explains the higher error rates in the two-choice procedure. However, Hino and Lupker did not provide any additional statistical analyses (e.g., RT distribution analyses) in support of their explanation.

Gibbs and Van Orden (1998) investigated phonological (homophone) effects in the two-choice and the go/no-go procedures. They argued that stimulus effects are distorted by the laboratory tasks used by researchers. Whereas the overall pattern of phonological effects was the same for the go/no-go and the two-choice procedure, error rates to words were much lower in the go/no-go procedure than in the two-choice procedure. Gibbs and Van Orden claimed that the go/no-go task "provides more time for word dynamics to run toward coherent states" (Gibbs & Van Orden, 1998) relative to the two-choice procedure, in which subjects are more likely to misclassify the word stimulus as a nonword. Along similar lines, some authors have made statements such as "the paradigms appear to be qualitatively distinct in terms of the cognitive demands and processes involved" (Jones, Cho, Nystrom, Cohen, & Braver, 2002, p. 301).

Perea et al. (2002) reexamined the size of the word-frequency effect in the go/no-go and two-choice procedures. Unlike Hino and Lupker (1998), Perea et al. found additive effects of word-frequency and task procedure (i.e., shorter RTs in the go/no-go task than in the two-choice task). However, a post hoc analysis showed that words that yielded high error rates also had longer

RTs in the go/no-go procedure relative to the two-choice procedure, thus providing some support for Hino and Lupker's claim (see also Perea, Rosa, & Gómez, 2003, for converging evidence). Perea et al. (2002) also found that the speed-up in responses to word targets when preceded by associatively related words relative to when they were preceded by unrelated words (e.g., *table–CHAIR* vs. *mouse–CHAIR*) was about the same size in the two tasks.

Perea et al. (2002) offered two possible explanations for their findings in the framework of a generic evidence accumulator model (no formal models were implemented). The first one is that subjects might use a lower criterion for "word" responses in the go/no-go task. However, moving the "word" criterion toward the starting point would also increase the probability of a false positive (i.e., an error to a word stimulus; see Stone & Van Orden, 1993). Perea et al. (2002) found no significant differences between the error rates to nonwords in the two procedures. The second explanation suggests that the accumulation of evidence is faster in the go/no-go procedure. The effect of having a higher rate of evidence accumulation would be a decrease in the RT and in the error rate for words relative to the two-choice task, as some of the research has found. More important, increasing the rate of evidence accumulation for words does not affect the response probabilities for nonwords (see Stone & Van Orden, 1993, Table 6).

Diffusion Model

In contrast with much of the research described above, we use a quantitative framework to examine different models, some in which components of processing vary from one procedure to the other and others in which processing remains unaltered. The diffusion model (Ratcliff, 1978, 2002; Ratcliff, Gomez, & McKoon, 2004; Ratcliff & Rouder, 1998, 2000) is a model of the processes involved in making simple two-choice decisions (but it is not a model of the lexical, perceptual, or memory processes that are the basis for the decision). The different parameters of the model are related to different components of processing, and fitting the model to data allows separation of the rate of evidence entering the decision from the decision criteria and from nondecisional components of processing.

The diffusion model assumes that decisions are characterized by the noisy accumulation of information over time from a starting point toward one of two response criteria or boundaries, as in Figure 1C, where the starting point is labeled *z* and the boundaries are labeled *a* and *0*. When one of the boundaries is reached, a response is initiated. 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, in lexical decision, for a high-frequency word the value of the drift rate toward the "word" boundary would be large. There is noise (variability) in the process of accumulating information so that processes with the same drift rate do not terminate at the same time (leading to RT distributions) and do not always terminate at the same boundary (thus producing errors). This is called *within-trial variability*. Figure 1C shows one process, with the drift rate represented by the arrow and the accumulation of noisy information represented by the jagged line.

Components of processing are assumed to be variable across trials, and the assumption of such variability allows the model to account for differences in RTs between correct and error responses (Luce, 1986). Variability in drift rate across trials leads to slow errors, and variability in starting point leads to fast errors (Ratcliff & Rouder, 1998; Ratcliff et al., 1999). Drift rate is assumed to be normally distributed across trials with standard deviation η, and starting point is assumed to be uniformly distributed with range s_z.

Nondecisional components of processing such as encoding and response execution are not part of the decision process. These are combined in the diffusion model into one component with mean

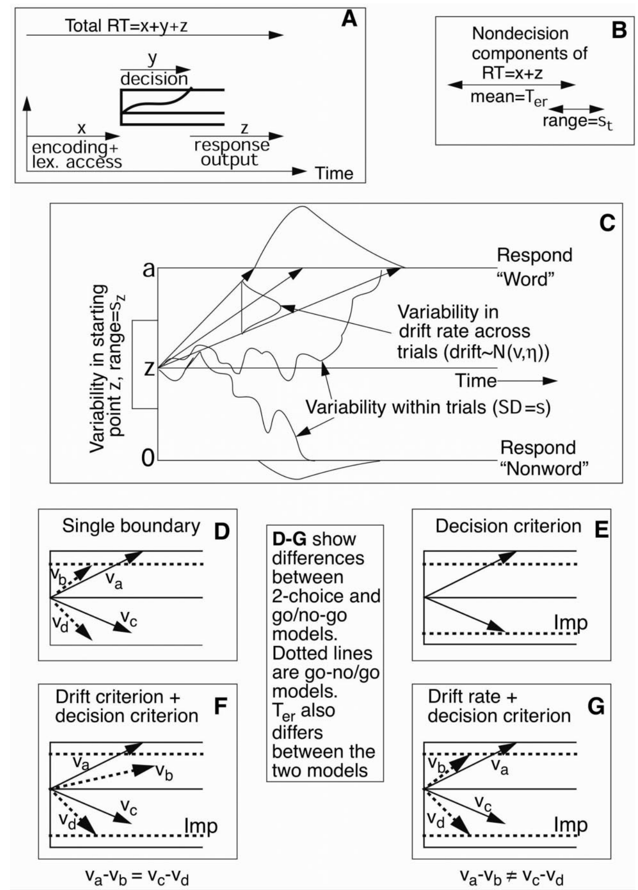


Figure 1. Panel A shows a representation of the sequence of events in a trial of a dual-choice task in which the stimulus is presented until a response is made. Panel B represents the nondecisional components of the response time (RT), which have a mean expressed by the T_{er} parameter and a range expressed by the s_t parameter. Panel C illustrates the diffusion model. The parameters represented in Panel C are a = boundary separation; z = starting point; s_z = variability in starting point across trials; v = drift rate; η = variability in the drift rate across trials; and variability in drift rate within a trial. Panels D to G (Imp = implicit boundary) show representations of the models of the go/no-go task. Panel D illustrates the single boundary model of the go/no-go task with z, T_{er}, and the drift rates as free parameters. Panel E illustrates the decision criteria model of the go/no-go task; it assumes an implicit negative decision boundary and a, z, and T_{er} as free parameters. Panel F illustrates the drift criterion model of the go/no-go task; it assumes an implicit negative decision boundary and a, z, T_{er}, and a constant added to all drift rates as free parameters. Panel G illustrates the drift rate model of the go/no-go task; it assumes an implicit negative decision boundary and a, z, T_{er}, and drift rates as free parameters.

T_{er} (see Figure 1B). The nondecisional component of processing is assumed to have variability across trials, and it is assumed to be uniformly distributed with range s_t. The effect of variability in the nondecisional component of processing depends on the mean value of drift rate (Ratcliff & Tuerlinckx, 2002). With a large value of mean drift rate, variability acts to shift the leading edge of the RT distribution shorter than it would otherwise be (by as much as 10% of s_t). With smaller values of drift rate, the effect is smaller (see also Balota & Spieler, 1999; Ratcliff, Gomez, & McKoon, 2004). The standard deviation in the distribution of the nondecisional component of processing is typically less than one quarter of the standard deviation in the decision process; therefore, the combination of the two (convolution) will have little effect on distribution shape and on the standard deviation in the distribution predicted from the decision process (Ratcliff & Tuerlinckx, 2002, Figure 11). For example, if $s_t = 100$ ms ($SD = 28.9$ ms) and the standard deviation in the decision process is 100 ms, the combination (square root of the sum of squares) is 104 ms. With variability in the nondecisional component of processing, Ratcliff and Tuerlinckx (2002) showed that the diffusion model could fit data with considerable variability in .1 quantile RTs across experimental conditions.

In sum, the parameters of the diffusion model correspond to the components of the decision process as follows: z is the starting point of the accumulation of evidence, a is the upper boundary, the lower boundary is set to 0, η is the standard deviation in mean drift rate across trials, s_z is the range of the starting point across trials, and s_t is the range of nondecisional components of processing across trials. For each different stimulus condition in an experiment, it is assumed that the rate of accumulation of evidence is different and so each has a different value of drift, v. 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 2 to produce exactly the same fits of the model to data).

Diffusion Models of the Go/No-Go Task

In the experiments presented below, subjects participated in both go/no-go and two-choice lexical decision tasks. In modeling, we jointly fit the two-choice diffusion model and a go/no-go model to the data from both tasks. We developed four go/no-go diffusion models that represent hypotheses about differences in processes between two-choice and go/no-go lexical decision. These models differ in which components of processing are the same in the two-choice task and the go/no-go task and which ones differ. In one model, we assume that there is only one decision boundary whereas in the other three models we assume an implicit negative decision boundary that is used to make the decision to withhold the response (see Ratcliff, 1988, 2006, for a similar notion of implicit boundaries applied to the response signal paradigm). Within the three models with implicit boundary, we go from assumptions of minimal differences between go/no-go and two-choice procedures to assumptions of more complicated differences between the two.

We assume that there are response-execution and strategic components that do change from one procedure to the other (as is commonly agreed; see Gordon, 1983; Pachella, 1974; Perea et al., 2002; Peressotti & Grainger, 1995). Within the diffusion model, this corresponds to changes in T_{er} (which includes the duration of the response execution stage) and changes in the a and z parameters (representing the decision criteria). These parameters were free to vary between the tasks in all of the models presented here except for the *single boundary model*, which does not include the a parameter. The go/no-go variants shown in Table 1.

Single Boundary Model

This model is designed to be a diffusion model implementation of accumulator models proposed for the go/no-go task (see, e.g., Grainger & Jacobs, 1996; Smith, 2000; Sperling & Dosher, 1986) in which the one decision boundary is associated with the go response (see Figure 1D). The drift rates are free parameters that were allowed to differ between the two procedures because the model with fixed drift rates across procedures failed badly, even at a qualitative level. When we describe the drift rate model, we explain the implications of allowing drift rates to vary across procedures.

Decision Criteria Model

The simplest of the implicit negative boundary models is one in which it is assumed that only response execution (T_{er}) and the strategic components (a and z) of the lexical decision task change across procedures. Core processes, represented by drift rates, remain constant (see Figure 1E). T_{er} is allowed to differ between the two tasks for this and the next two models because of the different response requirements (one vs. two responses).

Drift Criterion Model

The drift criterion model allows the T_{er}, a, and z parameters to differ across task as in the decision criteria model, but in addition, it assumes that there is a bias in the accumulation of information toward the decision criteria in the go/no-go task relative to the two-choice task. This is implemented in the model by adding (or subtracting) a constant to all of the drift rates from the two-choice task (cf. Ratcliff, 1985, Figure 2; Ratcliff et al., 1999, Figure 32; Ratcliff, 2002; Ratcliff & Smith, 2004; Ratcliff, Thapar, & McKoon, 2003). Note that this is not a change in discriminability, because it is the difference (which is constant in this case) between the drift rates between positive and negative items rather than the absolute value that determines discriminability[1] (see Figure 1F); this is exactly analogous to moving the criterion in signal detection theory.

Drift Rate Model

The *drift rate model* has free parameters T_{er}, a, z, and drift rates, and it assumes that the underlying cognitive processes (e.g., lexical processing in the lexical decision task) vary from the two-choice task to the go/no-go task. This is based on proposals by Perea et al. (2002), who argued that lexical processes are more efficient in the go/no-go task compared with the two-choice task. In the diffusion model, the assumption of better extraction of information due to more efficient lexical processing in the go/no-go task is imple-

[1] The difference between two drift rates divided by the between-trial variability, η, is a measurement analogue to d' (Ratcliff, 1978).

Table 1
Parameter Invariance and Free Parameters for the Models of the Go/No-Go Lexical Decision Task Relative to the Diffusion Model Fits to the Two-Choice Lexical Decision Task

	Parameter							
Model	a	T_{er}	η	s_z	Drift rates	s_t	z	No. free parameters
1	Removed	Free	Fixed	Fixed	Free (3 FP)	Fixed	Free	5
2	Free	Free	Fixed	Fixed	Fixed	Fixed	Free	3
3	Free	Free	Fixed	Fixed	Constant added (1 FP)	Fixed	Free	4
4	Free	Free	Fixed	Fixed	Free (3 FP)	Fixed	Free	6

Note. Model 1 refers to the single boundary model, Model 2 refers to the decision criteria model, Model 3 refers to the drift criterion model, and Model 4 refers to the drift rate model. FP = free parameters.

mented by allowing the magnitudes of the drift rate parameters to be larger in the go/no-go task relative to the two-choice task (see Figure 1G).

Overview of the Experiments

The six experiments presented in this article were designed to provide direct comparisons between the two-choice and the go/no-go tasks. For each subject, half of the experimental blocks were go/no-go trials, and the other half were two-choice trials. The first four experiments manipulated the most commonly examined factor in visual-word recognition, word frequency; Experiment 5 manipulated numerosity in a discrimination task; and Experiment 6 manipulated word frequency and repetition in a recognition memory task.

Experiment 1

Method

Subjects. Twenty Northwestern University undergraduates participated in this experiment for credit in an introductory psychology class. All subjects for Experiments 1 to 4 came from the same pool.

Materials. A set of 400 words of four or five letters were selected from the Kučera and Francis (1967) list. There were 200 low-frequency words (1 to 6 occurrences per million) and 200 medium-frequency words (8 to 20 occurrences per million). The number of orthographic neighbors (Coltheart's *N*; see Coltheart, Davelaar, Jonasson, & Besner, 1977) and number of letters were matched in each frequency group. (To obtain enough error RTs for adequate modeling, we used medium- rather than high-frequency words; see Ratcliff, Gomez, & McKoon, 2004.) Three Northwestern undergraduate students screened all words to eliminate proper names and words that they did not know. Four hundred nonwords were created by randomly replacing one letter of four- or five-letter words of similar frequencies that were not used in the experiment (any legitimate words created from this substitution were eliminated). Words and nonwords were matched on the number of orthographic neighbors.

Design. Task (go/no-go, two-choice) and word frequency (low, medium) were varied within subjects. Each subject was given a total of 800 experimental trials: 400 word trials and 400 nonword trials. Half of the trials used the go/no-go procedure, and the other half used the two-choice procedure. Word and nonword stimuli were counterbalanced across subjects so that if a particular letter string was presented in one of the two-choice blocks to one subject, it would be presented in one of the go/no-go blocks to the next subject. The order of the task was also counterbalanced: Half of the subjects performed the go/no-go task first, and the other half performed the two-choice task first.

Procedure. Stimuli (strings of letters) were presented in lowercase on a PC screen, with responses collected from the keyboard. Stimulus presentation and response recording were controlled by a real-time computer system. Subjects were instructed to decide whether each string of letters was or was not an English word. They were told that there would be two conditions: the *one-finger* (go/no-go task) and *two-finger* (two-choice task) conditions. Subjects were instructed that in the one-finger condition, they should press the */?* key with the index finger of their right hand if the string of letters on the screen was a word, and to "just wait for the next letter string" if the string of letters was not a word. Subjects were told that in the two-finger condition, they should press the */?* key for "word" responses and the *Z* key for "nonword" responses. In the two tasks, the stimulus item remained on the screen until a response was made or until 1,600 ms had elapsed. Subjects were instructed to make their responses as quickly as possible, while trying not to make too many errors. There was a 500-ms intertrial interval. RTs were measured from the onset of the letter string until the subject's response. Each subject received a different random order of stimuli.

The first two blocks of 32 trials were for practice. Half of the subjects practiced the go/no-go task in the first block and the two-choice task in the second block, whereas the other half practiced in the reverse order. The first five experimental blocks were of the same task as the second practice block; then there was a task switch and a new practice block was run, followed by the last five experimental blocks.

Results

In this and subsequent experiments, lexical decision latencies less than 250 ms or greater than 1,500 ms were excluded from the analysis (less than 1% of all responses). Mean lexical decision latencies and response probabilities were calculated across individuals and were submitted to separate analyses of variance (ANOVAs), each of which had two within-subject factors (word frequency and procedure) and a between-subjects factor (task order). The mean lexical decision latencies and response probabil-

Table 2
Summary of Results for Experiments 1 to 4

	Error RT		Correct RT		Probability of “word” responses		Correct RT at .1 quantile	
Stimulus type	Choice	Go/no-go	Choice	Go/no-go	Choice	Go/no-go	Choice	Go/no-go
Experiment 1								
Medium frequency	755 (28)		655 (16)	622 (13)	.946 (.010)	.966 (.004)	519 (10)	482 (7)
Low frequency	764 (45)		704 (18)	698 (13)	.819 (.019)	.852 (.014)	537 (11)	506 (9)
Nonwords	768 (31)	740 (22)	702 (25)		.089 (.011)	.076 (.009)	574 (15)	
Experiment 2 (word go/no-go task)								
Medium frequency	689 (37)		667 (12)	644 (9)	.879 (.016)	.930 (.013)	547 (12)	527 (7)
Low frequency	731 (31)		702 (14)	688 (10)	.719 (.022)	.816 (.022)	547 (13)	540 (7)
Nonwords	691 (19)	587 (16)	735 (20)		.142 (.010)	.161 (.031)	588 (13)	
Experiment 3 (nonword go/no-go task)								
Medium frequency	817 (41)	831 (32)	712 (15)		.921 (.008)	.897 (.015)	575 (10)	
Low frequency	814 (26)	837 (31)	751 (15)		.808 (.020)	.738 (.028)	583 (12)	
Nonwords	825 (25)		800 (18)	817 (22)	.169 (.025)	.107 (.024)	541 (13)	536 (15)
Experiment 4 (accuracy instructions)								
Medium frequency	856 (43)		657 (16)	609 (13)	.899 (.013)	.941 (.011)	511 (11)	475 (8)
Low frequency	785 (28)		712 (18)	666 (14)	.716 (.022)	.791 (.018)	531 (12)	494 (9)
Nonwords	712 (23)	671 (21)	736 (20)		.098 (.011)	.107 (.011)	538 (13)	
Experiment 4 (speed instructions)								
Medium frequency	634 (33)		565 (14)	557 (11)	.869 (.014)	.945 (.008)	444 (11)	438 (8)
Low frequency	625 (22)		598 (16)	608 (13)	.666 (.017)	.813 (.016)	458 (14)	450 (9)
Nonwords	587 (25)	597 (20)	633 (15)		.186 (.018)	.169 (.015)	475 (11)	

Note. Values are means, with standard errors in parentheses. Response times (RTs) are in milliseconds.

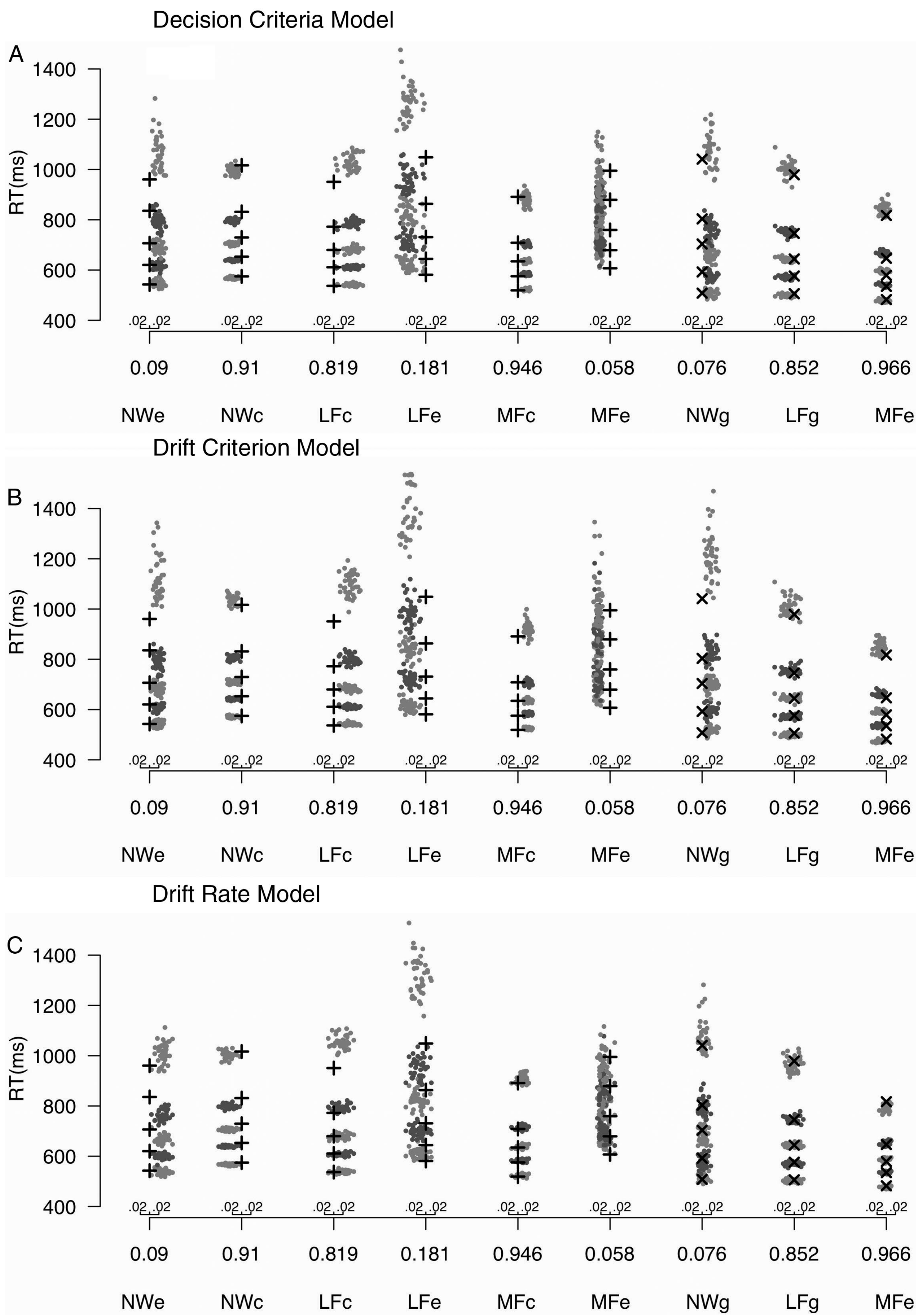
ities are presented in Table 2. Unless otherwise noted, all significant effects had p values less than the .05 level.

The procedure (go/no-go vs. two-choice) did not yield significant differences in the mean RT for correct responses to words, $F(1, 18) = 1.89$, $p = .18$, $\eta_p^2 = .095$. The mean RT was 33 ms shorter in the go/no-go task than in the two-choice task for medium-frequency words, but this difference was much smaller for low-frequency words (6 ms), yielding a significant Task × Word Frequency interaction, $F(1, 18) = 5.00$, $\eta_p^2 = .217$. This interaction also reflected a larger word-frequency effect in the go/no-go task than in the two-choice task (76 vs. 49 ms, respectively). Overall accuracy for words was higher in the go/no-go task than in the two-choice task (.90 vs. .87), $F(1, 18) = 13.10$, $\eta_p^2 = .421$, and accuracy was higher for medium-frequency words than for low-frequency words (.95 vs. .81), $F(1, 18) = 136.57$, $\eta_p^2 = .421$.

The accuracy data show similar patterns to the mean RT data. Overall accuracy for words was higher in the go/no-go task than in the two-choice task (.90 vs. .87), $F(1, 18) = 13.10$, $\eta_p^2 = .421$, and accuracy was higher for medium-frequency words than for low-frequency words (.95 vs. .81), $F(1, 18) = 136.57$, $\eta_p^2 = .884$.

To examine RT distributions, we used the RTs from each subject for each condition (medium-frequency words, low-frequency words, and nonwords crossed with correct and error responses) to estimate five quantile RTs: the .1, .3, .5, .7, and .9 quantiles. These quantiles were averaged across subjects (e.g., Ratcliff, 1979; Vincent, 1912) to form group RT distributions. The .1 quantile of the RT distribution represents the starting point or leading edge of the distribution. The distance between points represents the spread of the distribution. The leading edge of the group RT distributions (.1 quantile) was about 35 ms shorter in the go/no-go task than in the two-choice task, $F(1, 18) = 5.91$, $\eta_p^2 = .247$, and this effect did not interact with word frequency, $F(1, 18) = 1.60$, $p = .222$, $\eta_p^2 = .08$. The lack of main effect of task on the mean RTs occurred because the onset and the spread of the RT distributions were different for the two tasks: The go/no-go task

Figure 2 (opposite). The three panels show the empirical .1, .3, .5, .7, and .9 quantiles for the response time (RT) distributions in Experiment 1. The + signs are quantile RTs plotted against accuracy values calculated for the two-choice data with the accuracy range plotted on the x-axis (−.02 to +.02). The × signs are the quantile RTs for go/no-go data. The different panels represent the fits of the different models: the decision criteria model (A); the drift criterion model (B); and the drift rate model (C). The gray blobs show variability from Monte Carlo simulations based on the model. NWe = error responses to nonwords; NWc = correct responses to nonwords; LFc = correct responses to low-frequency words; LFe = error responses to low-frequency words; MFc = correct responses to medium-frequency words; MFe = error responses to medium-frequency words; NWg = go responses to nonwords; LFg = go responses to low-frequency words; MFg = go responses to medium-frequency words.



Decision Criteria Model
A
Drift Criterion Model
B
Drift Rate Model
C
RT(ms)
1400
1200
1000
800
600
400
.02 .02
0.09
0.91
0.819
0.181
0.946
0.058
0.076
0.852
0.966
NWe
NWc
LFc
LFe
MFc
MFe
NWg
LFg
MFe

produced more spread out RT distributions and shorter onsets. Figure 2 shows the results for Experiment 1. The three panels show the empirical RT distributions in Experiment 1 (the data points presented in the three panels are the same, and the model fits vary from panel to panel). The + signs are quantile RTs plotted against accuracy values calculated for the two-choice data, and the × signs are the quantile RTs for go/no-go data. Within each panel, there is a column of points for each combination of response (correct in two-choice, error in two-choice, and go in go/no-go) and type of item (two levels of word frequency and nonwords). The positions of the signs on the *y*-axis represent the RT at the five quantiles with the response probability as the label on the *x*-axis. The different panels represent the fits of the different models: Top panel, the decision criteria model; middle panel, the drift criterion model; and bottom panel, the drift rate model. (The gray blobs show variability from Monte Carlo simulations based on the models and are discussed later.)

The order in which the tasks were performed had an effect on the mean RT for the two-choice task. For those subjects who performed the go/no-go task first followed by the two-choice task, the mean RT for the two-choice task was 654 ms, whereas for those who performed the task in the reverse order, the mean RT was 706 ms. In contrast, the mean RT in the go/no-go task was very similar (662 and 658 ms) for the two task orders. This is reflected in the interaction between task and task order, which approached significance, $F(1, 18) = 3.83$, $p = .06$, $\eta_p^2 = .176$.

In sum, the go/no-go task produced shorter mean RTs for medium-frequency words, but not for low-frequency words, than the two-choice task (see Hino & Lupker, 1998; Perea et al., 2003, for a similar result). Also, the go/no-go task produced RT distributions with larger spread for correct responses (in particular for low-frequency words) and shorter onsets than the two-choice task (see Figure 2). The RT distributions for error responses have larger spreads (and have longer mean RTs) than the RT distributions for correct responses in both tasks and for all of the stimulus types.

Modeling and Discussion

To fit the diffusion model to the data, we minimized a likelihood chi-square statistic (G^2) (Ratcliff & Smith, 2004; Ratcliff & Tuerlinckx, 2002) by adjusting the parameter values using a general SIMPLEX minimization routine. The data that were entered into the minimization routine for each of the six experimental conditions (three levels of lexicality and two of task) were the accuracy values and the five quantile RTs averaged across subjects for correct and error responses. Fitting averaged data is an appropriate procedure for fitting the diffusion model. In previous research (Ratcliff, Thapar, et al., 2004; Ratcliff, Thapar, & McKoon, 2001; Ratcliff et al., 2003; Thapar, Ratcliff, & McKoon, 2003), fits to averaged data provided similar parameter values to parameter values obtained by averaging across fits to individual subjects. The quantile RTs were fed into the diffusion model, and for the RTs at the five quantiles, the model generated the predicted cumulative probability of a response by that point in time. Subtracting the cumulative probabilities for each successive quantile from the next higher quantile yields the proportion of responses between each quantile. These are the expected values for the chi-square computation, which are compared with the observed proportions of responses between the empirical quantiles. The observed proportions of responses for the quantiles are the product of the response probabilities and 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). The observed and expected proportions were multiplied by the number of observations to produce expected frequencies. The G^2 statistic has the advantage of being closely related to the Bayesian information criterion (BIC), and minimizing one minimizes the other. The model with the lowest BIC can be considered the model that jointly maximizes descriptive accuracy (goodness of fit) and parsimony (small number of free parameters). The statistics are defined as follows:

$$\mathrm{BIC} = -2[\Sigma N_j p_i \ln(\pi_i)] + M\ln(N)$$

$$G^2 = 2\Sigma N_j p_i \ln(p_i/\pi_i),$$

where p_i and π_i are the proportion of observations in the *i*th bin for the empirical data and the prediction of the model, respectively, and $M\ln(N)$ is the penalizing term related to the number of free parameters (M; which is relevant because all of the models under consideration here have different numbers of free parameters) and the sample size (N; the number of observations).

The three panels of Figure 2 show the data from Experiment 1. Each panel shows the fits of a different model (the single boundary model was not included). The blobs represent the result of a Monte Carlo simulation using the model with the best fitting parameters. The offset of each of the points that make the blob from the data points along the *x*-axis represents the miss of the model's predictions in accuracy, whereas the offset from the data points on the *y*-axis represents the miss of the model in latency at the different quantiles. The size of the blob represents an estimate of the standard error according to the model (see Table 3 for the standard error for each quantile according to the data). Hence, an overlap between the blobs from the Monte Carlo simulation and the data points (+ and × symbols) indicates an adequate fit.

Single boundary model. This model allowed the T_{er}, drift rate, and z parameters to vary freely from the two-choice to the go/no-go task but kept the variability parameters (η, s_z, and s_t) constant. This model has the highest BIC value for this experiment (3,392; see Table 4). It could not adequately fit the data: The model predicts higher response probabilities for nonwords than those observed and a larger spread in the distributions for all stimulus types than the ones observed (the results are not presented in Figure 2 because the predicted .9 quantiles are off the scale used to present the data). It is not possible to find a combination of parameters that modifies this model's predictions to match the qualitative pattern of results: If the starting point position (z) or the mean drift rate values are altered to reduce the response probability, the spread of the RT distribution for that response increases.

Decision criteria model. This model assumes that drift rates are identical across tasks so that the quality of the information extracted from the stimulus is the same in two-choice and go/no-go tasks. The a, z, and T_{er} parameters are free to vary between the two-choice and the go/no-go task data, whereas the drift rates and the variability parameters (η, s_z, and s_t) are fixed. This model has the smallest BIC value for this experiment (3,333). The fits of the decision criteria model are within .05 for all response probabilities

Table 3
Two Standard Errors for the Quantiles of the Response Time Distributions in the Go/No-Go Lexical Decision Task

	Quantiles for "word" responses					Quantiles for "nonword" responses				
Stimuli	.1	.3	.5	.7	.9	.1	.3	.5	.7	.9
Experiment 1 (two-choice)										
Medium-frequency words	8	7	10	14	26	27	57	78	96	128
Low-frequency words	9	12	16	24	56	57	32	49	76	153
Nonwords	21	22	22	43	113	7	6	9	13	29
Experiment 1 (word go/no-go)										
Medium-frequency words	8	8	9	13	23					
Low-frequency words	9	11	14	21	45					
Nonwords	11	11	14	20	39					
Experiment 2 (two-choice)										
Medium-frequency words	8	8	9	15	28	67	77	106	151	182
Low-frequency words	10	11	14	27	28	36	50	63	140	196
Nonwords	17	21	29	44	55	7	7	9	16	32
Experiment 2 (word go/no-go)										
Medium-frequency words	7	7	8	13	27					
Low-frequency words	8	8	11	22	45					
Nonwords	12	13	18	27	61					
Experiment 3 (two-choice)										
Medium-frequency words	7	7	8	11	32	27	37	45	60	34
Low-frequency words	11	10	13	17	31	18	20	27	95	33
Nonwords	11	12	12	18	30	7	7	9	16	32
Experiment 3 (nonword go/no-go)										
Medium-frequency words						21	23	31	40	88
Low-frequency words						34	43	59	89	178
Nonwords						8	8	9	13	28
Experiment 4 (two-choice accuracy)										
Medium-frequency words	24	29	34	43	56	38	44	51	69	124
Low-frequency words	22	24	27	35	52	61	82	100	128	141
Nonwords	31	38	46	56	87	27	28	33	43	96
Experiment 4 (go/no-go)										
Medium-frequency words	18	20	25	36	53					
Low-frequency words	16	17	21	28	57					
Nonwords	37	38	55	71	148					
Experiment 4 (two-choice speed)										
Medium-frequency words	27	25	29	33	43	31	33	37	47	104
Low-frequency words	21	23	25	28	42	45	48	54	93	130
Nonwords	35	39	49	57	84	21	21	25	32	70
Experiment 4 (speed)										
Medium-frequency words	28	38	67	85	94					
Low-frequency words	16	16	20	24	39					
Nonwords	32	36	48	67	151					

Note. Values are in milliseconds.

Table 4
Parameters of the Models and BIC Values for the Lexical Decision Task Experiments

Model	No. parameters	Parameter a	T_{er}	η	s_t	Drift_N	Drift_L	Drift_M	p_o	s_z	$a–z$	$a(G)$	$a(G)–z(G)$	$T_{er}(G)$	d_c	d_l	d_m	G^2	$M\ln(N)$	BIC
									Experiment 1											
1 Bound	15	.152	.483	.180	.067	−.352	.091	.305	.003	.000	.058		.063	.439	−.453	.160	.998	3,297	95.954	3,392
Des. C.	13	.125	.490	.088	.004	−.240	.147	.279	.002	.156	.053	.125	.057	.436				3,250	83.160	3,333
Drift C.	14	.124	.491	.077	.014	−.243	.137	.269	.029	.147	.051	.122	.068	.418	.052			3,250	89.557	3,339
Drift R.	16	.124	.486	.073	.004	−.229	.123	.238	.001	.146	.052	.122	.066	.423	−.213	.182	.329	3,246	102.351	3,348
									Experiment 2											
Des. C.	13	.097	.452	.097	.033	−.245	.114	.259	.000	.164	.042	.101	.040	.411				3,128	83.2	3,211
Drift C.	14	.097	.452	.077	.037	−.247	.100	.243	.000	.159	.041	.099	.047	.398	.054			3,127	89.6	3,216
Drift R.	16	.098	.451	.091	.040	−.240	.093	.243	.000	.159	.042	.098	.046	.405	−.220	.157	.319	3,125	102.4	3,228
									Experiment 3											
Des. C.	13	.103	.467	.058	.016	−.215	.096	.207	.021	.165	.064	.114	.060	.474				3,341	83.2	3,425
Drift C.	14	.110	.473	.120	.046	−.241	.132	.258	.002	.171	.068	.122	.055	.497	.019			3,341	89.6	3,430
Drift R.	16	.109	.477	.121	.045	−.255	.136	.265	.008	.178	.068	.121	.054	.500	−.214	.149	.276	3,340	102.4	3,443
									Experiment 4											
Des. C.	17	.135	.449	.124	.030	−.265	.096	.262	.001	.171	.058	.114	.049	.435				6,884	120.5	7,004
Speed		.086									.035	.105	.036							
Drift C.	18	.135	.448	.122	.030	−.256	.104	.266	.001	.171	.060	.114	.050	.432	−.001			6,884	127.6	7,011
Speed		.087									.037	.104	.036							
Drift R.	20	.131	.449	.106	.036	−.244	.070	.226	.016	.167	.056	.109	.059	.424	−.234	.164	.346	6,873	141.8	7,015
Speed		.085									.035	.096	.042							

Note. BIC = Bayesian information criterion. Parameters are as follows: a = boundary separation; T_{er} = nondecision components of the response time (RT); η = variability in drift rate across trials; s_t = range of the nondecision components of the RT; Drift_N = drift rate for nonwords; Drift_L = drift rate for low-frequency words; Drift_M = drift rate for medium-frequency words; p_O = probability of outliers; s_z = variability in starting point across trials; $a–z$ = distance between starting point z and the positive boundary; $a(G)$ = a parameter in the go/no-go task; $a–z(G)$ = distance between the starting point z and the positive decision boundary in the go/no-go task; $T_{er}(G)$ = T_{er} parameter for the go/no-go task; dc = constant added to all drift rates from two-choice to go/no-go in the drift criterion model, and for the drift rate model, dc represents the drift rate for nonwords; dl and dm = drift rates for low-and medium-frequency words for go/no-go in the drift rate model. Models of the go/no-go task are as follows: 1 Bound = single boundary model (no negative boundary for go/no-go; T_{er}, drift rates, and z free between tasks); Des. C. = negative decision criteria model (a and T_{er} free between tasks with implicit negative decision boundary); Drift C. = drift criterion model (T_{er}, a, z, and drift criterion free between tasks with implicit negative decision boundary); Drift R. = drift rate model (T_{er}, a, z, and drift rates free between tasks with implicit negative decision boundary).

(within two standard errors)[2] and within two standard errors of most of the RT data, including the RT at the .1 quantile (see Figure 2, top panel). The condition with the largest misses is error responses to low-frequency words, for which the model predicts a larger spread than the one found in the empirical data (this is the case also for the other models). The fits of this model are accomplished with a shorter T_{er} in the go/no-go task (by 54 ms) and a larger distance between the starting point and the positive decision boundary (.004). The behavior of these parameters can be interpreted as support for the notion of a less complex response execution stage in the go/no-go task and slightly more conservative decision criteria in the go/no-go task compared with the two-choice task.

Drift criterion model. This model assumes an implicit negative decision boundary and a change in the drift criterion across tasks. This means that drift rates are allowed to change as long as the differences among the drift rates are constant (i.e., the discriminability between words and nonwords is the same; cf. signal detection theory). In addition to the drift criterion, which is a constant added to all drift rates, the T_{er}, a, and z parameters are also free to vary between the two-choice task and the go/no-go task. The BIC value for this model is 3,339, which indicates that the extra free parameter did not significantly improve the fit to the data relative to the decision criteria model. The fits of the drift criterion model are very similar to those of the decision criteria model (see Figure 2, middle panel, for the fits of this model): The response probabilities are adequately fitted for all conditions, and the latency at the different quantiles, for the most part, fitted within two standard errors of the data. Most of the parameters of this model behave in expected ways. The T_{er} parameter was shorter for the go/no-go task (by 73 ms), and the drift rates across tasks "tilt," or bias, toward the word boundary (drift criterion = .052). The

[2] Estimating the variability (*SE*) for the quantiles and the response probabilities can be done in different ways (e.g., bootstrapping, generating data from the model, or calculating the *SE* directly from the data; see Ratcliff, Gomez, & McKoon, 2004). Here we used the quantiles for each subject as the random variable, and then we calculated the *SE* across subjects.

decision criteria parameters, *a* and *z*, modulate the bias toward the "word" decisions; the distance from the starting point to the word boundary (*a*–*z*) increased across task (.017), but the distance between the two boundaries decreased slightly (–.002). The behavior of the free parameters in the model can be interpreted the same way as in the decision criteria model: There was a shorter response execution stage and a more conservative decision criterion for the go/no-go task relative to the two-choice task. In addition, the drift criterion increased, biasing all of the drift rates to be slightly more positive.

Drift rate model. This model assumes an implicit negative decision boundary and changes in the drift rates between tasks (the previous model is a special case of this model). The assumptions are consistent with changes in the core components of the lexical decision process. As in the other models, the T_{er}, *a*, and *z* parameters are also free to vary between the two-choice task and the go/no-go task. The BIC value for this model is 3,348, the highest among the models that assumes an implicit negative decision boundary. This reflects the fact that the free drift rates did not significantly improve the fits relative to the cost of the extra parameters. This can be seen in Figure 2C, where it is difficult to visually differentiate the fits of this model from those of the decision criteria model (Panel A) and the drift rate criterion model (Panel B). The *a*, *z*, and T_{er} parameters change by very similar amounts as in the drift criterion model discussed above (see $a(G)$, $z(G)$, and $T_{er}(G)$ columns in Table 4). The differences in the drift rates from the two-choice task to the go/no-go task are more positive overall, but the changes in drift rate are greater for medium-frequency words than for low-frequency words.

In sum, the assumption of an implicit decision boundary provides a better account of the data than the single decision boundary model. Changes in the nondecisional components of the RT (T_{er} parameter) from their values for the two-choice task combined with changes in the decision criteria (the *a* parameter) were able to successfully fit the data from the go/no-go task.

Experiments 2 and 3

In Experiment 1, the items remained on the screen until the subject responded or 1.6 s had elapsed. Hence, it was possible that after a process hit the implicit negative boundary, a second comparison process could have been performed on some trials using the stimulus on the screen to encourage the second comparison, thus contaminating the data. To reduce the chance that subjects would engage in this rechecking process, we set stimulus exposure duration to 100 ms in Experiments 2 and 3. Note also that previous research with short and masked presentation times has provided evidence for stationary drift rate processes (drift rate is constant and is assumed to be produced from a short-term memory representation of the stimulus), so the diffusion model with constant drift rate would be the preferred way of modeling processing in this task (Ratcliff, 2002; Ratcliff & Rouder, 2000; Ratcliff & Smith, 2004; Smith, Ratcliff, & Wolfgang, 2004; Thapar et al., 2003).

In Experiment 1, the correct response probabilities to words were significantly higher in the go/no-go task than in the two-choice task. This significant improvement in accuracy was not observed for nonwords. This indicates that the advantage in performance in the go/no-go task might be related to decision processes rather than to lexical access processes. To further explore this, we had subjects respond to words in the go/no-go task in Experiment 2 (as in Experiment 1) and respond to nonwords in Experiment 3.

Method

Subjects. Two new groups of 21 Northwestern University undergraduates took part in this experiment.

Materials and procedure. The materials were the same as in Experiment 1. The procedure was also the same, with the following exceptions. At the beginning of each trial, the sequence "> <" was presented for 100 ms on the center of the screen. Then, the target stimulus was presented (always in lowercase) for 200 ms, after which the screen was cleared. The following trial started either 500 ms after a response was made or 500 ms after the 1,600 ms allowed for responding. Subjects were instructed to respond as quickly and as accurately as they could. As in Experiment 1, half of the subjects performed the go/no-go task first, and the other half performed the two-choice task first. Practice trials were presented in the same way as in Experiment 1.

In Experiment 2, subjects in the go/no-go task were instructed to respond (by pressing the */?* key) when the string of letters on the screen was an English word and to refrain from responding when the stimulus was not an English word. In Experiment 3, subjects in the go/no-go task were instructed to respond (by pressing the *Z* key) when the string of letters was not an English word (i.e., a nonword) and to refrain from responding when the letter string was an English word.

Results

One of the subjects from Experiment 2 was removed from this analysis because he or she failed to follow the instructions. Mean lexical decision latencies for correct responses and response probabilities were calculated across individuals, as in Experiment 1, and are presented in Table 2. The data from the experiments (Experiment 2: word go/no-go task; Experiment 3: nonword go/no-go task) were submitted to separate ANOVAs, each of which had two within-subject factors (task and word frequency) and a between-subjects factor (task order).

For correct word responses in Experiment 2 (word go/no-go task), subjects were marginally faster in go/no-go blocks than in two-choice blocks, for the mean RT (18 ms), $F(1, 19) = 3.21$, $p = .09$, $\eta^2_p = .162$, and nonsignificantly faster for the RT at the .1 quantile (13 ms), $F(1, 19) = 1.58$, $p = .22$, $\eta^2_p = .083$. For Experiment 3 (nonword go/no-go task), there was no significant effect of task for either mean RT or RT at the .1 quantile (Fs < 1). In Experiment 2, the effect of word frequency was significant for the mean RT, $F(1, 19) = 101.77$, $\eta^2_p = .843$, and for the .1 quantile, $F(1, 19) = 7.83$, $\eta^2_p = .292$, but the interaction between frequency and task was not significant for RT, $F(1, 19) = 2.25$, $p = .15$, $\eta^2_p = .106$, and approached significance for the .1 quantile, $F(1, 19) = 3.60$, $p = .07$, $\eta^2_p = .159$.

For both experiments, subjects made more errors to low-frequency than to medium-frequency words: word go/no-go (Experiment 2), $F(1, 19) = 77.11$, $\eta^2_p = .802$; nonword go/no-go (Experiment 3): $F(1, 20) = 79.73$, $\eta^2_p = .799$. But the most important finding was that the effect of task was different in

Experiment 2 than in Experiment 3. In Experiment 2, in which the word go/no-go task was performed, accuracy for words was higher in the go/no-go blocks than in the two-choice blocks, $F(1, 19) = 13.10$, $\eta^2_p = .408$; Task × Frequency interaction, $F(1, 19) = 5.46$, $\eta^2_p = .223$; whereas in Experiment 3, in which the nonword go/no-go task was performed, accuracy for words was higher in the two-choice task than in the go/no-go task: It changed from .92 in the two-choice task to .90 in the go/no-go task for medium-frequency words and from .81 in the two-choice task to .75 in the go/no-go task for low-frequency words: task, $F(1, 20) = 13.40$, $\eta^2_p = .401$; Task × Frequency interaction, $F(1, 20) = 4.46$, $\eta^2_p = .182$. The order in which the tasks were performed had no effect on the response probabilities or the latency data (all Fs < 0.1).

In sum, the results of Experiment 2 (word go/no-go task) essentially mimicked those of Experiment 1 (i.e., somewhat faster responding and higher accuracy in the go/no-go task than in the two-choice task). The data in Experiment 3 (nonword go/no-go task) showed an increase in the response probabilities to the overt response (nonword response) in the go/no-go task relative to the two-choice task, but there was no effect of task on the latency data.

Modeling and Discussion

We used the same modeling procedure as for Experiment 1. The parameter values and the fits are presented in Table 4 and in Figure 3 for Experiment 2 and in Figure 4 for Experiment 3. The figures have the same format as in Experiment 1.

For the go/no-go task in both experiments, the single boundary model produced poor fits both for response probabilities to words and for the shape of the RT distributions (the fits were so poor that they are not presented in Figure 3). For this reason, we do not consider this model further and we discuss only the models with an implicit negative decision boundary.

Decision criteria model. In this model, a, z, and T_{er} parameters are free to vary between the two-choice and the go/no-go tasks, but the drift rates are the same. This model provides good fits to the quantiles of the RT distribution and the response probabilities for the two experiments; further, it has the smallest BIC value for the two experiments (3,211 for Experiment 2 and 3,425 for Experiment 3). As in Experiment 1, the model predicts a larger spread than the observed one for the error RT distributions for low-frequency words. For the data from Experiment 2, the model accomplishes the good fits with approximately the same values of the z and a parameters across tasks and a shorter value of T_{er} (by 41 ms). In Experiment 3 (in which responses were made to nonwords), boundary separation increased by .011 from the two-choice to the go/no-go task, and the starting point decreased by .004. In addition, T_{er} increased by a nonsignificant 7 ms, which is different from the decrease obtained in Experiments 1 and 2. The behavior of these parameters does not provide strong support for the notion of a less complex response execution stage in the go/no-go task and may indicate a bias toward "word" responses. It also indicates a more conservative decision criterion in the go/no-go task for the no-go responses.

Drift criterion model. In this model we assume that the drift criterion changes across tasks, and so differences among the drift rates between words and nonwords are held constant. The drift criterion, T_{er}, a, and z parameters are free to vary between the two-choice task and the go/no-go task. The BIC values for this model are 3,216 for Experiment 2 and 3,430 for Experiment 3. This indicates that the extra free parameter did not significantly improve the fit relative to the decision criteria model. It is also important to note that in Experiment 2 the drift criterion is positive, whereas in Experiment 3 it is negative; in the two experiments, the drift rates are biased toward the overt response in the go/no-go task relative to the two-choice task. The nondecisional component (T_{er}) is shorter for the go/no-go task by 54 ms in Experiment 2 but longer by 26 ms in Experiment 3 relative to the T_{er} for the two-choice task. This suggests a bias in the output process toward a "word" response.

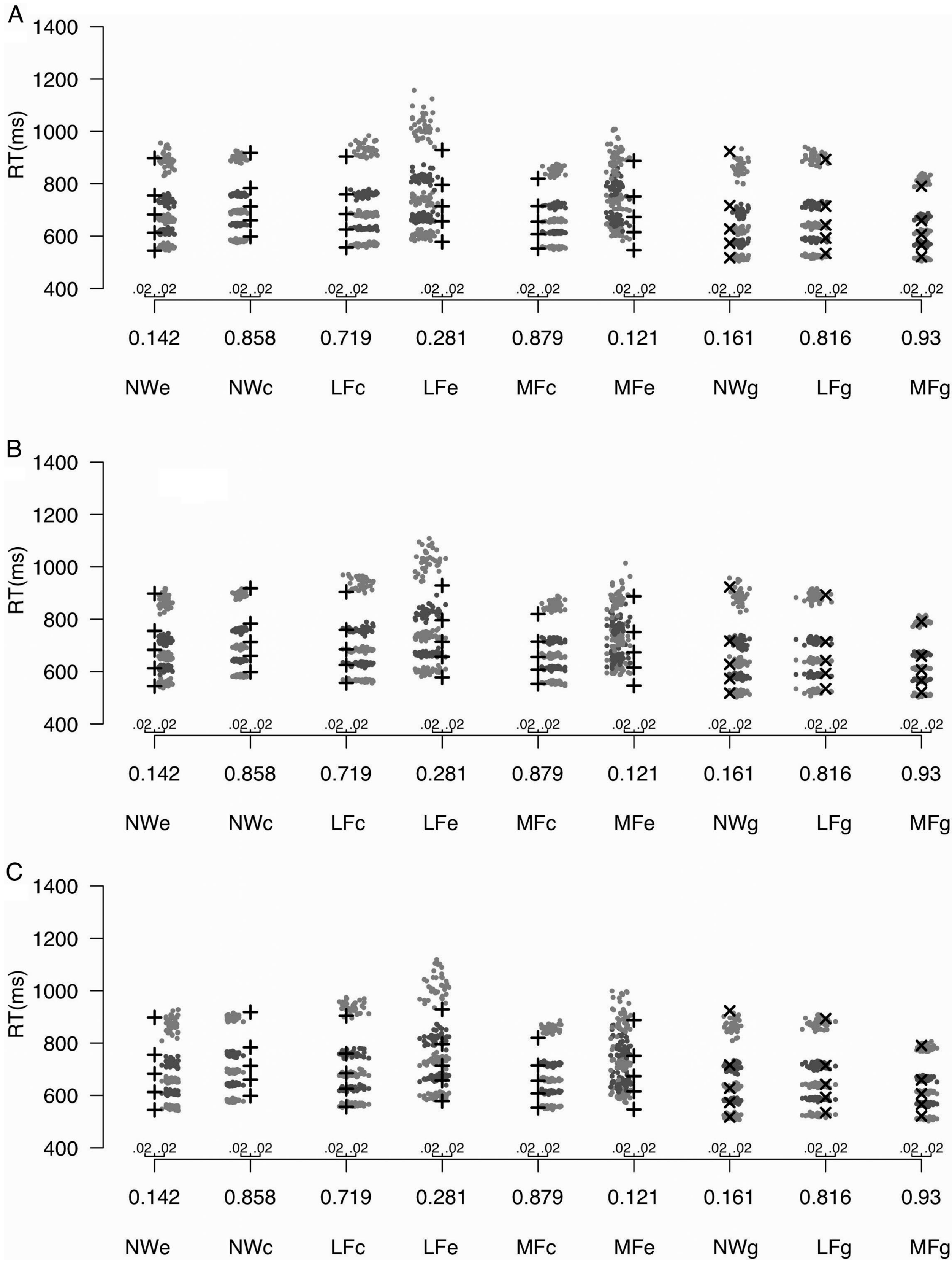
Drift rate model. This model assumes an implicit negative decision boundary and changes in the drift rates across task. Also, the T_{er}, a, and z parameters are free to vary between the two-choice task and the go/no-go task. The BIC values for this model are 3,228 for Experiment 2 and 3,443 for Experiment 3, which are higher than in the other two models. As in the previous experiment, the free drift rates did not improve the fits according to the BIC value. The a, z, and T_{er} parameters change by similar amounts as in the drift criterion model discussed above.

In sum, the pattern of results in Experiments 2 and 3, using a 100-ms presentation time for the stimulus items, resembles that of Experiment 1: higher response probabilities for the overt responses in the go/no-go task compared with the two-choice task, and shorter RTs at the .1 quantile for word stimuli in the go/no-go task. However, the effect of task on the spread of the RT distributions for words was attenuated in Experiment 2 relative to Experiment 1. Also, in Experiments 2 and 3, the a and z parameters were smaller than in Experiment 1. Nonetheless, the qualitative behaviors of the parameters of the three models that use an implicit boundary are consistent across experiments and support the notion of a bias toward the overt response in the go/no-go task rather than changes in the lexical or core processes across tasks.

Experiment 4

In Experiments 1 to 3, the models that include an implicit decision boundary produced substantially better fits than the model with only one boundary. In Experiment 4, we examined whether

Figure 3 (opposite). The three panels show the empirical .1, .3, .5, .7, and .9 quantiles for the response time (RT) distributions in Experiment 2. The + signs are quantile RTs plotted against accuracy values calculated for the two-choice data. The × signs are the quantile RTs for go/no-go data. The different panels represent the fits of the different models: the decision criteria model (A); the drift criterion model (B); and the drift rate model (C). The gray blobs show variability from Monte Carlo simulations based on the model. NWe = error responses to nonwords; NWc = correct responses to nonwords; LFc = correct responses to low-frequency words; LFe = error responses to low-frequency words; MFc = correct responses to medium-frequency words; MFe = error responses to medium-frequency words; NWg = go responses to nonwords; LFg = go responses to low-frequency words; MFg = go responses to medium-frequency words.


A
B
C
RT(ms)
1400
1200
1000
800
600
400
.02 .02
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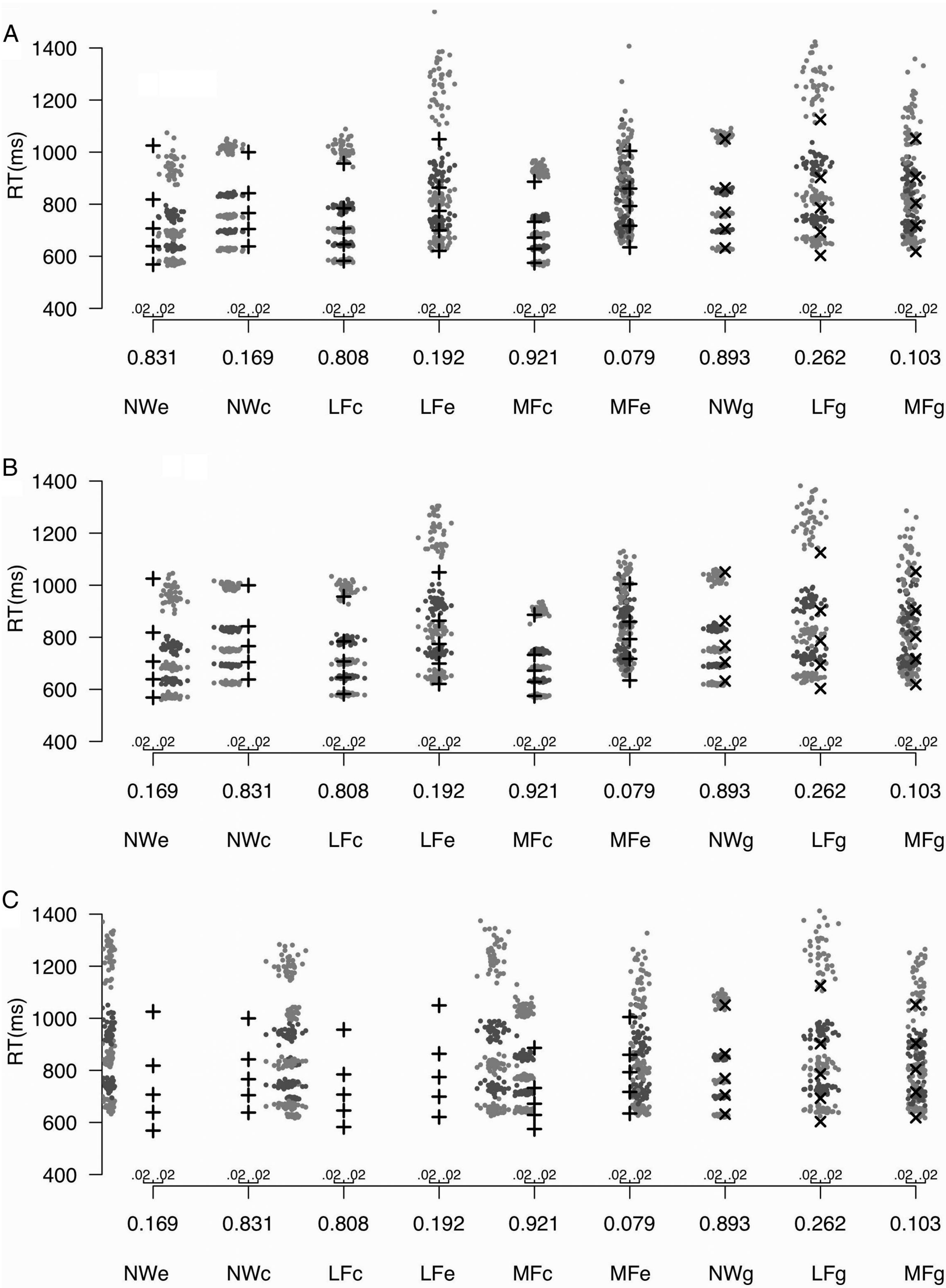
NWe NWc LFc LFe MFc MFe NWg LFg MFg


A
B
C
RT(ms)
1400
1200
1000
800
600
400
.02 .02
0.831 0.169 0.808 0.192 0.921 0.079 0.893 0.262 0.103
0.169 0.831 0.808 0.192 0.921 0.079 0.893 0.262 0.103
NWe NWc LFc LFe MFc MFe NWg LFg MFg

this implicit boundary in the go/no-go task behaves in a similar way as the explicit boundaries in the two-choice task. In this experiment, we instructed subjects to focus on either speed or accuracy, and we examined whether the speed–accuracy instructions affected the position of the explicit and implicit boundaries in the go/no-go task, even in the case of the implicit no-go decision.

Method

Subjects. A new group of 28 Northwestern University undergraduates took part in this experiment.

Materials and procedure. Sets of 640 words of four or five letters were selected from the Kučera and Francis (1967) list. There were 320 low-frequency words (1 to 6 occurrences per million) and 320 medium-frequency words (8 to 20 occurrences per million); the number of letters was matched in each frequency group. Six hundred forty nonwords were created by randomly replacing the vowels of four- or five-letter words (not used in the experiment) with other vowels.[3] The structure of the trials was the same as in the previous experiments.

Design. Task (go/no-go, two-choice), instructions (speed, accuracy), and word frequency (low, medium) were varied within subjects. Over 2 days, each subject was given a total of 1,280 experimental trials: 640 word trials and 640 nonword trials. Half of the trials used the go/no-go procedure, and the other half used the two-choice procedure. Word and nonword stimuli were counterbalanced across subjects so that if a particular letter string was presented in one of the two-choice blocks to one subject, it would be presented in one of the go/no-go blocks to the next subject. The blocks of trials alternated between two-choice and go/no-go tasks and between speed and accuracy instructions. In the speed blocks, subjects were told to emphasize speed over accuracy, and in the accuracy blocks, subjects were told to emphasize accuracy over speed. In each of the two sessions, there were eight experimental blocks with 80 trials each.

Results

RTs shorter than 250 ms or longer than 1,500 ms were excluded from the latency analyses (less than 1% of all responses). Mean lexical decision latencies and response probabilities were calculated across individuals and are presented in Table 2.

Medium-frequency words had a shorter mean RT than low-frequency words (by about 50 ms), $F(1, 27) = 287.96$, $\eta_p^2 = .914$; responses to words had a shorter mean RT in the go/no-go task than in the two-choice task (by about 40 ms), $F(1, 27) = 6.68$, $\eta_p^2 = .198$; and responses were shorter under speed instructions than under accuracy instructions (by about 80 ms), $F(1, 27) = 45.43$, $\eta_p^2 = .627$. The effect of word frequency was larger under accuracy instructions (57 ms) than under speed instructions (42 ms): interaction, $F(1, 27) = 6.14$, $\eta_p^2 = .185$. The task effect was a 47-ms-shorter overall RT for the go/no-go task in the accuracy condition as compared with almost no effect in the speed condition: Task × Instructions interaction, $F(1, 27) = 20.48$, $\eta^2{}_p = .421$.

RTs at the .1 quantile were shorter to medium-frequency words than to low-frequency words by about 15 ms, $F(1, 27) = 41.37$, $\eta_p^2 = .605$. RTs at the .1 quantile to words were shorter in the go/no-go task than in the two-choice task (these differences ranged from 12 to 36 ms), $F(1, 27) = 10.32$, $\eta_p^2 = .276$, and RTs at the .1 quantile to words under speed instructions were shorter than under accuracy instructions by about 40 ms, $F(1, 27) = 53.94$, $\eta_p^2 = .666$. The effect of word frequency was also larger under accuracy instructions than under speed instructions: interaction, $F(1, 27) = 3.83$, $p = .061$; $\eta_p^2 = .124$. For the .1 quantile, the instructions had a much greater effect on the two-choice task than on the go/no-go task: interaction, $F(1, 27) = 10.27$, $\eta_p^2 = .276$. This interaction reflects the fact that the difference between the go/no-go task and the two-choice task was quite large under accuracy instructions (about 500 ms), whereas it was quite small (less than 5 ms) under speed instructions. The other interactions did not approach significance.

In the two-choice task, correct RTs to nonwords were substantially shorter under speed instructions than under accuracy instructions, both in mean RT (about 100 ms), $F(1, 27) = 11.79$, $\eta_p^2 = .304$, and at the .1 quantile (about 60 ms), $F(1, 27) = 5.57$, $\eta_p^2 = .171$.

Medium-frequency words were responded to more accurately than were low-frequency words by a proportion of about .2, $F(1, 27) = 245.05$, $\eta_p^2 = .900$, and accuracy was higher in the go/no-go task than in the two-choice task, $F(1, 27) = 58.61$, $\eta_p^2 = .685$. The effect of word frequency was greater in the go/no-go task than in the two-choice task: interaction, $F(1, 27) = 24.24$, $\eta_p^2 = .473$, and the effect of task was greater under speed instructions than under accuracy instructions: interaction, $F(1, 27) = 6.56$, $\eta_p^2 = .196$. The other interactions did not approach significance.

Relative speed of correct versus incorrect responses. For words in the two-choice task, we found shorter mean RTs for the correct ("word") responses than for the incorrect ("nonword") responses (a 90-ms effect), $F(1, 27) = 33.31$, $\eta_p^2 = .552$. This effect was modulated by word frequency and the instructions: three-way interaction, $F(1, 27) = 4.87$. This interaction reflected that the difference between correct and incorrect RTs was substantially larger under accuracy instructions than under speed instructions (136 ms vs. 48 ms, respectively) and that these effects were greater for medium-frequency words than for low-frequency words (134 ms vs. 50 ms, respectively). For the nonwords, we found shorter latencies for the incorrect ("word") responses than

Figure 4 (opposite). The three panels show the empirical .1, .3, .5, .7, and .9 quantiles for the response time (RT) distributions in Experiment 3. The + signs are quantile RTs plotted against accuracy values calculated for the two-choice data. The × signs are the quantile RTs for go/no-go data. The different panels represent the fits of the different models: the decision criteria model (A); the drift criterion model (B); and the drift rate model (C). The gray blobs show variability from Monte Carlo simulations based on the model. NWe = error responses to nonwords; NWc = correct responses to nonwords; LFc = correct responses to low-frequency words; LFe = error responses to low-frequency words; MFc = correct responses to medium-frequency words; MFe = error responses to medium-frequency words; NWg = go responses to nonwords; LFg = go responses to low-frequency words; MFg = go responses to medium-frequency words.

[3] Note that the items used in this experiment included those used in Experiments 1 to 3, but some additional items were added, because in this experiment we had twice as many trials as in the previous experiments.

for the correct ("nonword") responses, $F(1, 27) = 6.08$, $\eta_p^2 = .184$, and this difference was similar under speed and accuracy instructions.

Discussion and Modeling

The speed–accuracy manipulation produced the expected pattern of results in both the two-choice and the go/no-go tasks: Speed instructions yielded lower accuracy (by about .05) and shorter RTs (by about 80 ms) than accuracy instructions. We now examine the fits of the diffusion model for the go/no-go data in the speed and the accuracy conditions. We expect to see more conservative decision criteria in the accuracy condition as opposed to the speed condition. In terms of the parameter values, we expect to observe smaller values of z and a in the speed condition than in the accuracy condition. In the modeling for the present experiment, we allow the position and starting point parameters (a and z) to vary across task and across instructions.

Figure 5 shows the fits and the data for the two-choice task for Experiment 4. In this figure, we present only the fits from the decision criteria model, which was the one with the lowest BIC. Responses in accuracy condition (top panel) and in speed condition (bottom panel) are adequately accounted for by the model. The parameter values are shown in Table 4, and as expected, the instruction manipulation produced differences in the values of the a and z parameters: Under accuracy instructions, a is .135 and z is .067, whereas for speed instructions a is .086 (.049 difference) and z is .051 (.016 difference). The magnitude of the effect of the instructions in the parameter values is smaller than that found by Wagenmakers, Ratcliff, Gomez, and McKoon (2007); however, the pattern is the same.

For the go/no-go task, we examined the three different models examined above (see Table 3 for parameter values and free parameters). The effect of the emphasis on speed or accuracy in the models is captured by changes in the distances between the starting point of the diffusion process and the decision boundaries, with shorter distances in the speed condition than in the accuracy condition.

As noted in the *Results* section, the effect of task on the .1 quantile was negligible under speed instructions, whereas it was quite large under accuracy instructions. Within the context of these models, this interaction can be accounted for with changes in the distance between the boundaries and the starting point. Assuming a constant drift rate, the .1 quantile for positive responses depends mostly on two parameters, T_{er} and z; when these two parameters

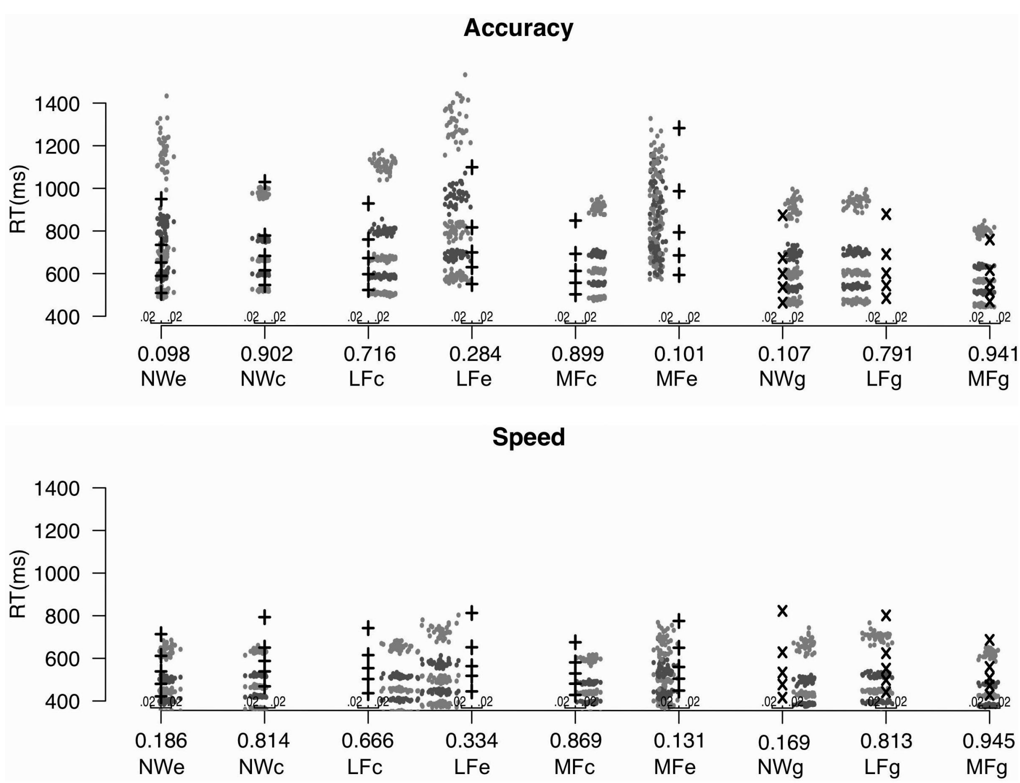


Figure 5. The two panels show the empirical .1, .3, .5, and .9 quantiles for the RT distributions in Experiment 4. The + signs are quantile response times (RTs) plotted against accuracy values calculated for the two-choice data. The × signs are the quantile RTs for go/no-go data. The gray blobs show variability from Monte Carlo simulations based on the decision criteria model. NWe = error responses to nonwords; NWc = correct responses to nonwords; LFc = correct responses to low-frequency words; LFe = error responses to low-frequency words; MFc = correct responses to medium-frequency words; MFe = error responses to medium-frequency words; NWg = go responses to nonwords; LFg = go responses to low-frequency words; MFg = go responses to medium-frequency words.

are free, these effects can cancel each other. For this experiment, if the effect of task is different for z_{sp} than for z_{ac}, and there is a change in T_{er} across task, then the interaction between task (two-choice vs. go/no-go) and instructions (speed vs. accuracy) will be observed at the .1 quantile.

Decision criteria model. As in the previous experiments, this model has the lowest BIC value (7,004). The starting point (z), the distance between boundaries (a), and the nondecisional component of the RT (T_{er}) are free to vary from the two-choice task to the go/no-go task, and the a and z parameters are allowed to vary from the speed to the accuracy conditions.

The .1 quantile of the RT distributions is again shorter in the go/no-go task than in the two-choice task. This effect is captured in this model by a change in the T_{er} parameter, which is shorter (by 14 ms) in the go/no-go task than in the two-choice task. The behavior of the a and z parameters indicates that the speed–accuracy instructions had an effect on the distance between the starting point and the positive decision boundary (a–z). This is because the effect of the speed–accuracy instructions is rather small in the a parameter in the go/no-go task whereas the effect in the z parameter is as large as in the two-choice task. Thus, the behavior of the parameters of this model supports the notion of shorter nondecisional components in the RT for the go/no-go task.

Drift criterion and drift rate models. The other two models under consideration show the same picture as the decision criteria model discussed above. In fact, the drift criterion parameter (BIC = 7,011) for the second model has a value of only .001. The a, z, and T_{er} parameters in the drift rate model also follow the same pattern as in the other two models. Also, as in the previous experiments, in the drift rate model all of the drift rates are more positive, especially the drift rate for medium-frequency words. The BIC value for the drift rate model is again the largest (7,015).

To summarize, in this experiment we explored the behavior of the implicit decision boundary with a speed–accuracy manipulation. With different sets of free parameters, the distance between the starting point and the explicit decision boundary does seem to change as a function of the instructions; also, the instructions seem to have a smaller effect on the distance between the starting point and the implicit decision boundary in the go/no-go task.

Experiment 5

This experiment was carried out to determine whether the pattern of results and parameter values found in the lexical decision experiments described above would be obtained in a nonlexical task. We chose a numerosity discrimination task like the one used by Espinoza-Varas and Watson (1994) and Ratcliff et al. (1999). On each trial of the experiment, an array of asterisks was presented on a computer screen, and the subjects' task was to decide whether the number of asterisks was high or low.

Performance in this type of task is a function of a single independent variable, the number of asterisks; for example, 30 asterisks within a 10 × 10 array is easier to classify as "low" than, say, 45 asterisks within the same 10 × 10 array. This task has advantages for our purposes: It generates many responses per condition, which yields stable RT distributions; in addition, by varying the difficulty of the tasks we create multiple drift rate conditions, which allows us to constrain model fitting.

Method

Subjects. Fourteen DePaul University undergraduates participated in this experiment for credit in an introductory psychology class.

Stimuli and procedure. The asterisks were presented in a 10 × 10 grid in the upper left corner of a computer monitor for 100 ms. They appeared as light characters on a dark background with high contrast. The number of asterisks was selected by randomly sampling from a uniform distribution with end points 31 and 70. An array of 50 asterisks or fewer was considered "low," and an array of 51 or more was considered "high"; subjects received accuracy feedback accordingly. This is different from the probablistic feedback provided in earlier studies (Espinoza-Varas & Watson, 1994; Ratcliff et al., 2001; Ratcliff et al., 1999). In each trial 2,000 ms was allowed for responding. After the 2,000 ms or once a response was made, there was a 500-ms intertrial interval. The computer monitors were driven by a real-time stimulus presentation system.

Design. Task (go/no-go, two-choice) and number of asterisks (from a uniform distribution with end points 31 and 70) were varied within subjects. Each subject was given a total of 1,080 experimental trials. Half of the trials used the go/no-go procedure, and the other half used the two-choice procedure. The go/no-go and two-choice blocks were grouped; half of the subjects were tested in the go/no-go procedure first, and the other half in the two-choice procedure first. Subjects were instructed to press the *?/* key for high and, in the two-choice procedure, the *Z* key for low. In the go/no-go procedure they were instructed to respond only to high numbers of asterisks and to not respond and wait for the next trial for low numbers of asterisks.

Results and Modeling

The data from 3 of the subjects showed that they were pressing the key that corresponded to the "low" response in some of the go/no-go trials. The data from these subjects are not used in these analyses. Also, RTs below 200 ms were eliminated from the data analysis (about 1.4% of all responses).

To reduce the number of experimental conditions, we collapsed the data according to the number of asterisks presented into eight groups with interval size of five (31 to 35, 36 to 40, etc). This experiment's task produced consistent effects of number of asterisks on latency and proportion of correct responses in both the go/no-go and the two-choice procedures. As the number of asterisks increased, the proportion of "high" responses increased. Similarly, as the number of asterisks became more extreme, the mean RT decreased (see Table 5 and Figure 1 [available in the online supplement]). The response probabilities and the mean RTs for "high" responses were submitted to separate ANOVAs with two within-subject factors: number of asterisks and procedure (go/no-go and two-choice). For the mean RT, only number of asterisks yielded significant differences, $F(7, 10) = 4.42$, $\eta_p^2 = .307$ (all other Fs < 1). For response proportion, number of asterisks, $F(7, 10) = 354.64$, $\eta_p^2 = .973$; procedure, $F(1, 10) = 22.57$, $\eta_p^2 = .693$; and the interaction, $F(7, 10) = 2.79$, $\eta_p^2 = .287$, yielded significant effects. To accommodate all of the data points from this experiment, the figures for this and the next experiment have a slightly different format than the ones presented before. Figure 6 shows

Table 5
Summary of Results for Experiments 5 and 6

	Error RT		Correct RT		Proportion of "large"/"old" responses		Correct RT at .1 quantile	
Stimulus type	Choice	Go/no-go	Choice	Go/no-go	Choice	Go/no-go	Choice	Go/no-go
Experiment 5								
66–70 asterisks	384 (39)		468 (11)	444 (19)	.916 (.019)	.985 (.007)	343 (9)	347 (9)
61–65 asterisks	456 (36)		485 (12)	459 (19)	.885 (.023)	.949 (.017)	345 (10)	342 (8)
56–60 asterisks	592 (24)		497 (15)	487 (23)	.817 (.017)	.933 (.016)	340 (10)	349 (11)
51–55 asterisks	531 (21)		524 (18)	539 (28)	.698 (.026)	.840 (.035)	355 (14)	348 (13)
46–50 asterisks	562 (23)	561 (27)	547 (22)		.475 (.024)	.617 (.049)	347 (17)	
41–45 asterisks	538 (27)	562 (30)	548 (19)		.311 (.022)	.389 (.045)	392 (15)	
36–40 asterisks	466 (23)	530 (50)	523 (14)		.160 (.025)	.218 (.035)	370 (10)	
31–35 asterisks	434 (29)	517 (80)	507 (13)		.100 (.025)	.104 (.032)	366 (9)	
Experiment 6								
High frequency (2)	678 (41)		572 (29)	623 (35)	.738 (.049)	.676 (.067)	421 (11)	430 (14)
High frequency (1)	661 (41)		600 (24)	654 (39)	.583 (.049)	.586 (.049)	430 (14)	448 (11)
High frequency (0)	647 (40)	681 (37)	621 (27)		.193 (.038)	.196 (.036)	446 (13)	
Low frequency (2)	689 (55)		556 (21)	594 (51)	.888 (.037)	.819 (.061)	432 (14)	416 (9)
Low frequency (1)	636 (54)		590 (24)	634 (41)	.754 (.046)	.726 (.054)	440 (14)	434 (8)
Low frequency (0)	681 (71)	710 (46)	636 (31)		.145 (.028)	.162 (.031)	444 (15)	

Note. Values are means, with standard errors in parentheses. Response times (RTs) are in milliseconds. In Experiment 5, 50 asterisks or fewer was considered small. The number in parentheses next to the stimulus type for Experiment 6 represents the number of presentations during the study phase.

quantile-probability functions for the averaged data in Experiment 5. The quantile-probability functions displayed in this figure better show the effects of the task on the latency and accuracy data simultaneously. As in the previous figures, the RTs at the .1, .3, .5, .7, and .9 quantiles are plotted along the *y*-axis; however, unlike in the previous figures, in this one the response proportions for each are plotted along the *x*-axis. The panels on the left correspond to "large" responses; the filled dots represent the data from the two-choice task, and the open dots represent the data from the go/no-go procedure. The panels on the right represent "small" responses in the two-choice procedure. The empirical data are the same across the three rows, but the fits of the models change across rows. The solid lines represent the fit of the model to the two-choice data, and the dashed lines represent the fit of the model to the go/no-go data. Also, as can be seen in the figure, the RT distributions for the go/no-go task were more spread out than the ones for the two-choice task.

The three models with implicit decision boundaries for the go/no-go task were fit to the latency and response proportion data from this experiment. The data that were used in the minimization routine for each of the 16 experimental conditions (eight levels of numerosity and two levels of task) were the accuracy values and the five quantile RTs averaged across subjects for both correct and error responses. Figure 6 shows quantile-probability functions for the data (open dots represent the go/no-go data and filled dots represent the two-choice data). The decision criteria model has three free parameters across procedure: T_{er}, a, and z. The drift criterion model has four free parameters across procedure: the same three as the decision criteria model plus the drift rate criterion. And the drift rate model has the same free parameters across procedure as the decision criteria model, plus all the drift rates.

Table 6 shows the best fitting parameters for the three models along with the BIC values. The three models produce good fits to the data, but the decision criteria model produces the best fit according to the BIC (1,301 for the decision criteria model; 1,303 for the drift criterion model; and 1,351 for the drift rate model). Hence, the conclusion from this experiment is similar to the one obtained for the lexical decision experiments: The go/no-go task seems to affect the decision criteria (parameters a and z) and the nondecisional components of the RT (T_{er} parameter), and in this experiment, it might bias the accumulation of evidence (drift criterion parameter).

Experiment 6

Experiment 6 was designed to provide data to allow the modeling to be extended to the domain of recognition memory. In this experiment, word frequency and the number of presentations during study were manipulated as in Ratcliff, Thapar, and McKoon (2004).

Method

Subjects. A new group of 17 DePaul University undergraduates took part in this experiment.

Stimuli. There were 800 high-frequency words, with frequencies from 78 to 10,600 per million (M = 325, SD = 645); 800 low-frequency words, with frequencies of 4 and 5 per million (M = 4.41, SD = 0.19); and 741 very low frequency words, with frequencies of 1 per million or no occurrence in Kučera and Francis's (1967) corpus. All of the very low frequency words did appear in the *Merriam-Webster's Collegiate Dictionary* (1990).

Procedure. The experiment consisted of 26 study–test blocks per session. Each study list consisted of 25 words, 4 high- and 4 low-frequency words presented once, and 4 high- and 4 low-frequency words presented two times. One very low frequency

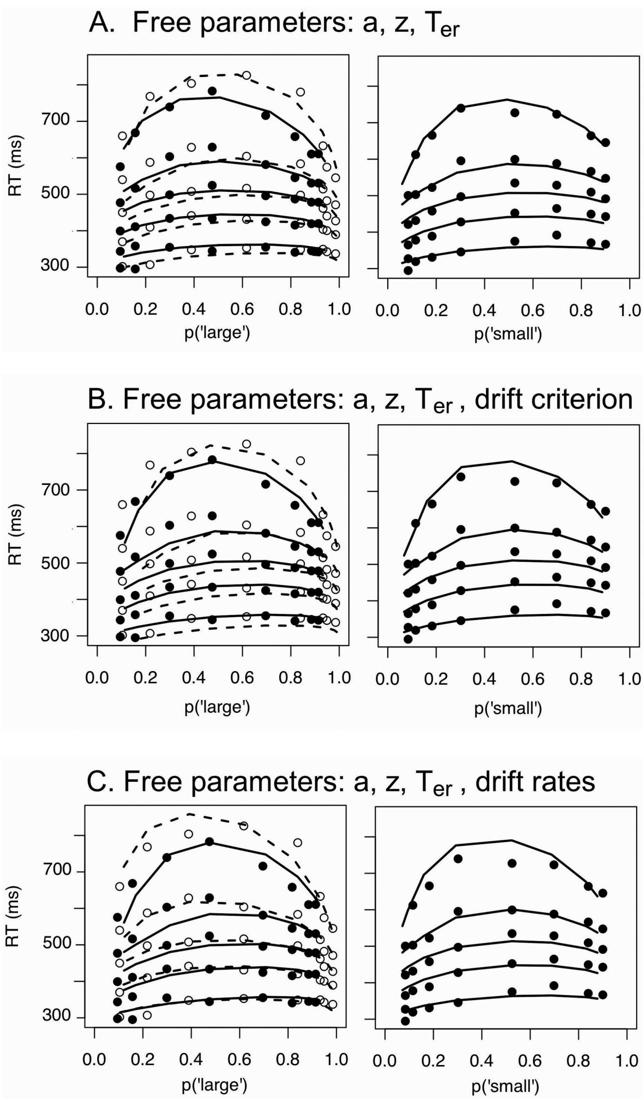


Figure 6. Quantile-probability functions for the averaged data in Experiment 5. The panels on the left correspond to "large" responses; the filled dots represent the data from the two-choice task, and the open dots represent the data from the go/no-go procedure. The panels on the right represent "small" responses in the two-choice procedure. The empirical data are the same across the three rows, but the fits of the models change. The solid line represents the fit of the model to the two-choice data, and the dashed line represents the fit of the model to the go/no-go data. The quantile-probability functions displayed in this figure better allow us to observe the effects of the task on the latency and accuracy data simultaneously. Given the large number of conditions, we use this displaying method instead of the confidence dots shown in the previous experiments. RT = response time.

word was presented as the final word in the study list. Each study word was displayed for 1,300 ms. The repeated words were presented with at least 2 other words intervening between presentations. Each test list consisted of the 17 studied words and 17 new words, the latter consisting of 8 high, 8 low, and 1 very low frequency word. In each test block, either the new very low frequency word was the first test item and the old very low frequency word was the second item, or vice versa; these very low frequency items were used as a buffer and hence were not part of the analysis presented below. To match the procedure used in the other experiments presented in this article, the test item was presented for 100 ms. In each trial 2,000 ms was allowed for responding. After the 2,000 ms or once a response was made, there was a 500-ms intertrial interval.

Thirteen of the study–test blocks used the two-choice procedure; subjects were instructed to respond by pressing the *?* key for old words and the *Z* key for new words. The other 13 blocks used the go/no-go procedure; subjects were instructed to respond by pressing the *?* key for old words and not to respond for new words. The go/no-go and two-choice blocks were grouped; half of the subjects were tested in the go/no-go procedure first, and the other half in the two-choice procedure first.

Results and Modeling

Out of the 17 subjects, 3 were not included in the present analysis because they failed to follow instructions. Responses shorter than 300 ms were not included in this analysis (about 2.3% of all responses).

Table 5 shows a summary of the results for this experiment, and Figure 2 (available in the online supplement) shows the proportion of "old" responses for each condition (the variable of interest in most recognition memory studies). The mean RT for correct responses and the proportion of correct responses for old items were submitted to separate ANOVAs with number of presentations during study (one vs. two), word frequency (high vs. low), and procedure (go/no-go vs. two-choice) as within-subject factors. The same dependent variables for correct responses to new items were submitted to separate ANOVAs with word frequency and procedure as within-subject factors. For the correct responses to old items, for the mean RT, significant differences were found only for the main effects of word frequency (shorter RTs to low-frequency words), $F(1, 13) = 6.29$, $\eta_p^2 = .326$, and number of presentations (shorter RTs for two presentations), $F(1, 13) = 16.27$, $\eta_p^2 = .556$. These same two factors were significant for proportion of correct responses: $F(1, 13) = 56.77$, $\eta_p^2 = .326$, for word frequency and $F(1, 13) = 39.05$, $\eta_p^2 = .326$, for number of presentations during study. In the ANOVAs for correct responses to new items, we found only marginal effects of word frequency on false alarms rates, which were lower for low-frequency words (.154) than for high-frequency words (.195), $F(1, 13) = 3.13$, $p = .10$; $\eta_p^2 = .194$, and also a marginal effect of frequency on correct RTs to new items, with shorter RTs for high- than for low-frequency words, $F(1, 13) = 3.16$, $p = .10$; $\eta_p^2 = .196$. Just like in the other experiments, the RTs for the go/no-go procedure have a larger spread than those for the two-choice procedure, as can be seen in Figure 7, which includes the data and the model fits that are discussed below.

These results replicate well-known patterns of results in recognition memory. Lower frequency words are easier to recognize than higher frequency words (e.g., Glanzer & Bowles, 1976; Gorman, 1961), and words that are presented more frequently during study are easier to recognize than words presented less frequently (e.g., Ratcliff & Murdock, 1976). The diffusion model assumes that the match between the probe and the memory representation maps into drift rate. For this exper-

Table 6
Parameter Values for Experiment 5, Numerosity Discrimination Experiment

			Drift rates											
Model and task	a	T_{er}	66–70	61–65	56–60	51–55	46–50	41–45	36–40	31–35	a–z	No. parameters	G^2	BIC
Decision criteria												17	1,183	1,301
Two-choice	.095	.290	.591	.467	.345	.178	.009	−.120	−.279	−.404	.048			
Go/no-go	.111	.263									.047			
Drift criterion												18	1,177	1,303
Two-choice	.100	.293	.608	.481	.336	.160	−.019	−.187	−.353	−.485	.049			
Go/no-go	.113	.259					Drifts in two-choice +.120				.049			
Drift rate												25	1,176	1,351
Two-choice	.100	.289	.510	.439	.305	.153	−.033	−.170	−.343	−.447	.048			
Go/no-go	.111	.261	.786	.608	.472	.264	.086	−.071	−.210	−.362	.056			

Note. In the decision criteria model, s_z = .163, η = .082, s_t = .246; in the drift criterion model, s_z = .175, η = .096, s_t = .244; in the drift rate model, s_z = .160, η = .093, s_z = .237. BIC = Bayesian information criterion.

iment, we allowed the drift rates to vary freely for each type of item (one-presentation low-frequency words, two-presentation low-frequency words, one-presentation high-frequency words, two-presentation high-frequency words, new high-frequency words, and new low-frequency words). The response proportions and the quantile RTs averaged across subjects for error and correct responses were entered into the minimization routine for each of the 12 experimental conditions (two levels of word frequency, three levels of the number of presentations, and two levels of task). Figure 7 shows the latency-probability functions for the data (open dots represent the go/no-go data and filled dots represent the two-choice data). The three panels show the same data but differ in the model used to fit the data. The solid lines represent the fits to the two-choice procedure, and the dashed lines represent the fits to the go/no-go procedure. The three models evaluated are the ones that contain an implicit negative ("low") boundary for the go/no-go task (the same models as in Experiments 1 to 5). The decision criteria model has three free parameters across procedures: T_{er}, a, and z. The drift criterion model has four free parameters across procedures: the same three as the decision criteria model plus the drift rate criterion. The drift rate model has nine free parameters, the same as the decision criteria model plus all of the drift rates.

Table 7 shows the best fitting parameters for the three models along with the BIC values. As in the previous experiments, the three models produce good fits to the data (this time the fits of the three models are visually indistinguishable). Nonetheless, the decision criteria model fits better (BIC = 666) than the other two models according to the BIC value (a difference of 6 and 36 from the drift criterion and drift rate models, respectively). The advantage in terms of BIC for the decision criteria model is because it is the model that has the fewest number of free parameters. Thus, the conclusion from this experiment for recognition memory is that the go/no-go task can be adequately modeled in the same way as for the lexical decision and numerosity discrimination experiments. The changes in the model between the go/no-go task and the two-choice task are in the placement of the decision criteria (parameters a and z) and in the duration of the nondecisional components of the RT (T_{er} parameter).

General Discussion

Across the six experiments presented in this article, we obtained values of accuracy, mean RT, and RT distributions for correct and error responses for both two-choice and go/no-go tasks. We found three robust effects that any model of the go/no-go task must explain: (a) There is an improvement in the accuracy rate for items associated with the overt response in the go/no-go task compared with the two-choice task; (b) the spread of RT distributions in the go/no-go task is larger than that in the two-choice task; and (c) there is a shift in the leading edge of the RT distributions from the two-choice task to the go/no-go task, with the .1 quantile for go responses from 10 to 30 ms shorter than the equivalent response in the two-choice task.[4] Because of the larger spread in the RT distributions in the go/no-go task and the reduction in the leading edge, the advantage of the go/no-go task may not always appear using mean RT as the dependent variable (e.g., in Experiments 1 and 2 the difference in the mean RT across tasks is less than 10 ms for low-frequency words).

The fits of the diffusion model to the data from the six experiments provide a good account of the two-choice tasks (see also Ratcliff, Gomez, & McKoon, 2004; Ratcliff, Thapar, & McKoon, 2001, 2004; Ratcliff, Thapar, et al., 2004). By implementing assumptions about the go/no-go task in the diffusion model, we were able to simultaneously account for data from the go/no-go task with some parameter invariance across tasks. The model fails only to fully account for error RT distributions for low-frequency words in Experiments 1 to 3. Specifically, the model predicts a larger spread than the one found in the data. There are several possible reasons for the misfit, and we discuss two. In data from tasks in which there is high accuracy (like the lexical decision task), the estimates of the error RT distributions have large confidence intervals. The second issue is that in our lexical decision experiments, we eliminated data with RTs longer than 1,600 ms,

[4] Although the effect of task at the .1 quantile did not occur in the nonword go/no-go experiment (Experiment 3), it did occur in four other word go/no-go experiments that are not included in this article. As we said earlier, it may be the case that this decrease in T_{er} occurs especially with word responses in the go/no-go task.

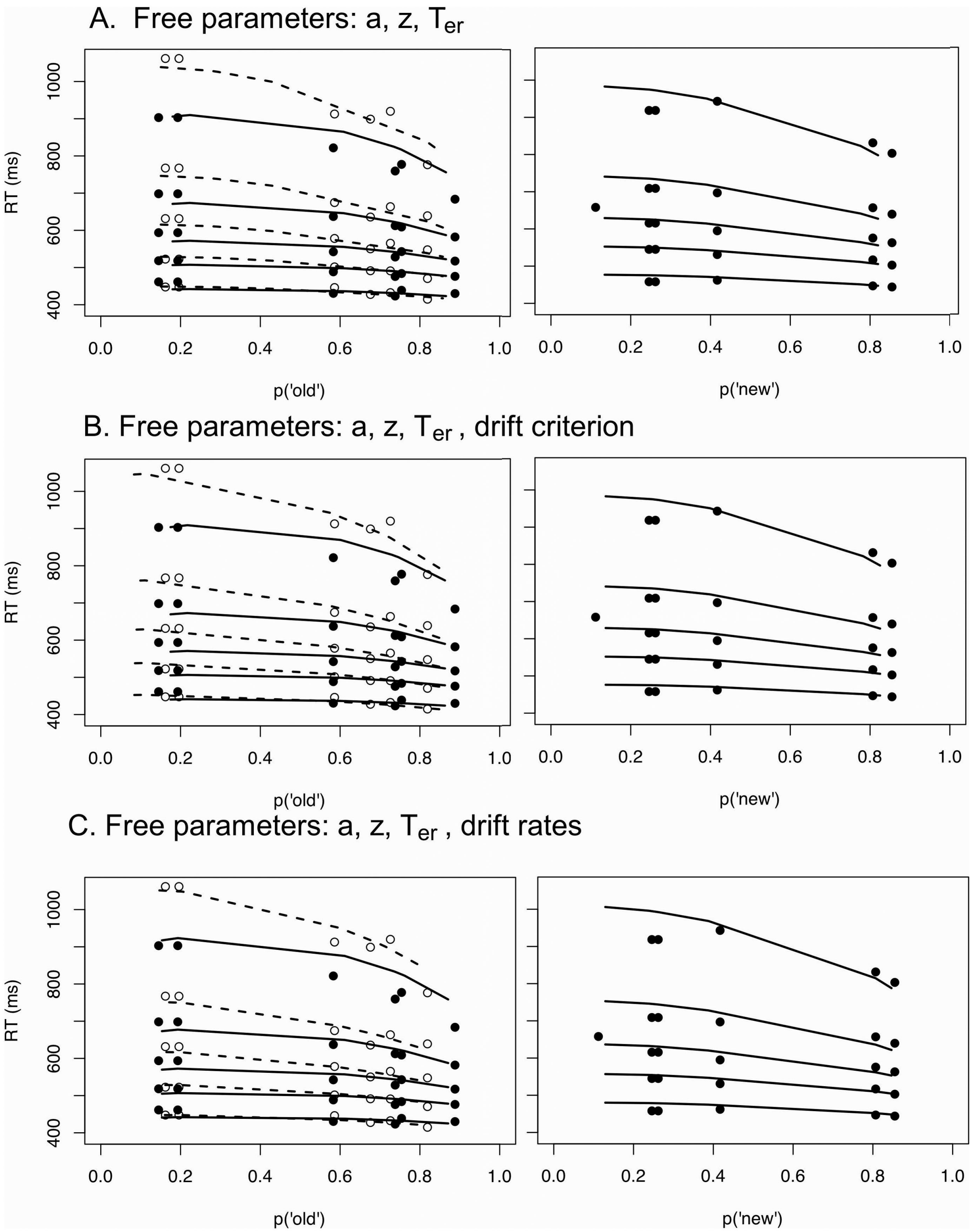


Figure 7. Quantile-probability functions for the averaged data in Experiment 6. The panels on the left correspond to "old" responses; the filled dots represent the data from the two-choice task, and the open dots represent the data from the go/no-go procedure. The panels on the right represent "new" responses in the two-choice procedure; in these right panels, the "new" responses to low-frequency two-presentation words are represented by a single point (the median), because there were not enough responses per subject to estimate the quantiles for the response time (RT) distribution. The empirical data are the same across the three rows, but the fits of the models change. The solid line represents the fit of the model to the two-choice data, and the dashed line represents the fit of the model to the go/no-go data.

Table 7
Parameter Values for Experiment 6, the Recognition Memory Experiment

Model and task	a	T_{er}	Drift rates HF(2)	HF(1)	HF(0)	HF(2)	HF(1)	HF(0)	$a–z$	No. parameters	G^2	BIC
Decision criteria										15	576	666
Two-choice	.111	.399	.136	.052	−.220	.252	.141	−.262	.048			
Go/no-go	.123	.367							.062			
Drift criterion										16	576	672
Two-choice	.111	.399	.125	.036	−.227	.246	.138	−.267	.048			
Go/no-go	.121	.355		Two-choice drifts			+.04		.070			
Drift rate										21	575	702
Two-choice	.114	.401	.136	.045	−.260	.267	.157	−.303	.048			
Go/no-go	.125	.367	.132	.068	−.205	.213	.149	−.263	.056			

Note. In the decision criteria model, s_z = .196, η = .010, s_t = .141; in the drift criterion model, s_z = .199, η = .010, s_t = .143; in the drift rate model, s_z = .210, η = .027, s_t = .137. BIC = Bayesian information criterion.

which was the time-out delay for no-go responses. This, of course, would produce RT distributions with shorter spreads.

In all of the fits, we kept the parameters that represent variability in processing constant across the two-choice and go/no-go tasks. It is reasonable to expect that the change in the parameter values would be along the same scale as changes in the main parameter; for example, if the drift rates change about 10% from one task to the other, then the η parameter would change by about 10% too. Such changes in the variability parameters would have negligible effects in the predictions of the model. Furthermore, the variability parameters have high variability associated with them (see Ratcliff & Tuerlinckx, 2002).

Our results suggest that the most parsimonious explanation within the framework of random-walk or diffusion models is that the go/no-go procedure is just a type of two-choice task in which one response is associated with one decision boundary and the other response is associated with the other decision boundary. The go/no-go task differs from the two-choice task in that there is only one observed response. Nonetheless, the decision not to respond (no-go) seems to be associated with an implicit choice (at an implicit decision boundary).

The model most commonly considered for the go/no-go task assumes that there is a single decision boundary associated with the go response and no boundary for no-go responses (see Smith, 2000; Sperling & Dosher, 1986). A similar approach is adopted by one of the most successful computational models of the lexical decision task, the multiple read-out model (Grainger & Jacobs, 1996). In this model, the go/no-go task is just a two-choice task without a decision criterion for no-go responses (see Grainger & Jacobs, 1996, p. 559). For nonword responses, Grainger and Jacobs assume a time criterion. This means the model would not be able to apply to Experiment 3 with nonwords as go responses.

The fits of our single boundary model were very poor across experiments, in terms of both response probabilities and the spread of the RT distributions. Given the poor quality of the fits, we can rule out the single decision boundary model as an account of the go/no-go task. Even when we allowed the a, z, T_{er}, and drift rate parameters to differ between the two-choice task and the go/no-go task, the single boundary model systematically missed the data in two critical ways: It overestimated the response probabilities, and it predicted RT distributions with much more spread than the data.

It might be thought that a single boundary model not constrained by the fits to the two-choice task could account for the data in the go/no-go task. We examined this possibility by allowing all nine parameters in the single boundary model to vary freely and fitted the single boundary diffusion model to the go/no-go data in the experiments. The model achieves fits similar to those of the implicit boundary models (jointly fitted with a two-choice model) by dramatically increasing the magnitude of the negative drift rate for no-go items (e.g., for Experiment 1, the drift rate for nonwords went from –.234 in the two-choice task to –.551 in the go/no-go task). That is, in this model, negative items would generate twice as much negative evidence in the go/no-go task as in the two-choice task. The model also dramatically increases the value of the variability in drift rate across trials relative to the two-choice task (from .09 in the two-choice task to .258 in the go/no-go task in Experiment 1). These parameter values are at the extremes of those found in other applications of the diffusion model, and indeed, there are obvious problems of interpretation of these values. The conclusion that the go/no-go task needed an implicit boundary is consistent with the conclusion from the fits of models to the response signal procedure, which showed that implicit boundaries are necessary to fit both the regular two-choice task and response signal data (Ratcliff, 2006).

The existence of an implicit negative decision is supported by neurological evidence (e.g., Liddle, Kiehl, & Smith, 2001; Sasaki, Gemba, Nambu, & Matsuki, 1993). Researchers have used the go/no-go procedure as a paradigm to study brain activation during operations such as error processing, response inhibition, and response competition. For example, Drewe (1975) showed that orbitofrontal lesions impair performance in the go/no-go task (these types of lesions also produce *environmental dependence*, which produces behaviors in which individuals are not able to resist using objects that are within reach). Along the same lines, intoxicated individuals show deficits in go/no-go performance (Finn, Justus, Mazas, & Steinmetz, 1999).

The issue of control has also been investigated with event-related brain potential (ERP) studies. No-go trials often produce a negative ERP component with a frontocentral scalp distribution known as N2. The N2 has been related to executive control mechanisms like inhibition and conflict detection. There has been some debate on how general this finding might be, with some researchers having failed to find it with auditory stimuli (see Falkenstein, Hoormann, & Hohnsbein, 2002; Falkenstein, Koshlykova, Kiroj, Hoormann, & Hohnsbein, 1995); however, it has been shown that if the auditory task is made difficult enough, the N2 emerges even in the auditory modality (Nieuwenhuis, Yeung, & Cohen, 2004). Functional MRI studies have shown similar results (e.g., Garavan, Ross, & Stein, 1999; Menon, Adleman, White, Glover, & Reiss, 2001). Activation during a no-go trial is consistent with inhibitory control. Also, there is an overlap between the regions of the brain related to error processing and those related to inhibitory control. This overlap is not perfect, however. For example, in no-go trials there is activation of the lateral parietal cortex, which does not show error-related activation, and therefore, it has been assumed that the lateral parietal cortex is associated only with inhibitory control.

These lines of research have shown that there is activation of brain areas related to response inhibition during no-go trials. This finding has been interpreted as a no-go response being an inhibition of a positive response; however, the interpretation that emerges from the fits of the diffusion model is slightly different: Subjects might be inhibiting the negative response after they have reached the implicit negative decision boundary.

Of note, the fits to the data from Experiment 4 show that the model with an implicit boundary can accurately account for the go/no-go data in a speed–accuracy manipulation. The parameters (namely a and z) behave in the predicted way: The implicit negative boundary changes its position depending on whether speed or accuracy is emphasized.

A more complex issue is which of the three models that incorporate the implicit decision boundary is the best? To choose among them we use three criteria: (a) Which model optimizes the trade-off between precision and parsimony (i.e., number of free parameters)? (b) Which model produces the smallest misses between the observed data and the predictions, and are any of the misses systematic (e.g., does a model tend to err in one direction for all conditions)? (c) Do parameter values behave in consistent ways as a function of the experimental manipulations? The answers to these three questions point to the decision criteria and drift criterion models as the best of the models considered here. These models support the notion that all that changes between the two-choice and go/no-go tasks is the peripheral components of the task.

An assumption made by some researchers is that the go/no-go procedure can provide a better tool to uncover the nature of cognitive processes. Our analysis indicates that the go/no-go procedure has rather limited benefits compared with the two-choice procedure. In fact, it is likely to be a less sensitive tool for research because it provides only half the number of conditions as a two-choice task.

To summarize, in this article we have evaluated, in the context of the diffusion model, several competing assumptions on the decision processes involved in the go/no-go task. We have demonstrated that the diffusion model successfully accounts for the data in both tasks. Furthermore, we have provided strong empirical and modeling evidence in favor of an implicit negative decision boundary for the no-go task. Finally, the modeling shows that the higher accuracy and faster responding in the go/no-go task is not due to less noisy processing or a better extraction of information. Instead, the go/no-go advantage seems to be due to a change in the decision criteria combined with a faster nondecisional component of processing.

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