

# The Hare and the Tortoise: Emphasizing Speed Can Change the Evidence Used to Make Decisions

Babette Rae and Andrew Heathcote  
University of Newcastle

Chris Donkin  
University of New South Wales

Lee Averell and Scott Brown  
University of Newcastle

Decision-makers effortlessly balance the need for urgency against the need for caution. Theoretical and neurophysiological accounts have explained this tradeoff solely in terms of the *quantity* of evidence required to trigger a decision (the “threshold”). This explanation has also been used as a benchmark test for evaluating new models of decision making, but the explanation itself has not been carefully tested against data. We rigorously test the assumption that emphasizing decision speed versus decision accuracy selectively influences only decision thresholds. In data from a new brightness discrimination experiment we found that emphasizing decision speed over decision accuracy not only decreases the amount of evidence required for a decision but also decreases the quality of information being accumulated during the decision process. This result was consistent for 2 leading decision-making models and in a model-free test. We also found the same model-based results in archival data from a lexical decision task (reported by Wagenmakers, Ratcliff, Gomez, & McKoon, 2008) and new data from a recognition memory task. We discuss implications for theoretical development and applications.

**Keywords:** evidence accumulation, speed accuracy tradeoff, response time, decision making, sequential sampling

Quantitative theories of decision making have provided insights not only into the cognitive processes that underpin choice but also into the associated neurophysiology and dozens of different topics in applied and clinical settings (e.g., Churchland, Kiani, & Shadlen, 2008; Forstmann et al., 2008; Gold & Shadlen, 2007; Ratcliff & McKoon, 1995; Ratcliff & Smith, 2004; Roitman & Shadlen, 2002; Rouder, 2000; Shurman, Horan, & Neuchterlein, 2005). There are several successful theories of simple decision making that differ in detail but share a common framework, called “sequential sampling”—the idea that information from the environment is steadily accumulated until sufficient evidence has been gathered to make a decision. Even though the models differ in detail, they often agree on substantive questions of interpretation (Donkin, Brown, Heathcote, & Wagenmakers, 2011).

Ratcliff’s (1978) diffusion model (see also Ratcliff & Smith, 2004) is the most influential and widely applied sequential sampling model. It describes stimulus processing as the noisy accumulation of evidence over time, and it applies to tasks in which a participant decides quickly between two alternatives, such as

whether a stimulus is brighter or darker than average. The diffusion process accumulates evidence about the stimulus by drifting between two thresholds—representing the two alternatives—with a response initiated when the accumulated evidence reaches either threshold. The three key components of the diffusion model are (a) the speed of information processing, quantified by drift rate,  $v$ ; (b) the response threshold, quantified by the separation between the boundaries,  $a$ ; and (c) the time taken for things other than the actual decision making, such as stimulus encoding and response execution, quantified by the nondecision parameter,  $t_{er}$ .

The linear ballistic accumulator (LBA; Brown & Heathcote, 2008) is a sequential sampling model of the “accumulator” class, with each choice alternative represented by a separate evidence accumulator. Analogous to Ratcliff’s (1978) diffusion model, the LBA assumes that evidence gathers in each accumulator according to a drift rate parameter and that a response is initiated as soon as the first accumulator reaches a threshold. In both models responses can be slowed in several different ways: by a threshold increase, by a decrease in the quality of information, and hence the rate of accumulation, or when nondecision time increases.

Part of the success of sequential-sampling models arises from their ability to separate the influences of different latent (not directly observed) cognitive processes that are conflated in observed data. Their ability has theoretical and practical implications. For example, older adults typically make slower decisions than younger adults; analysis with sequential sampling models has shown that this slowdown is often due to increased caution rather than poorer quality information (a change in threshold, not drift rate; Forstmann et al., 2011; Ratcliff, Thapar, & McKoon, 2007,

---

This article was published Online First May 5, 2014.

Babette Rae and Andrew Heathcote, School of Psychology, University of Newcastle; Chris Donkin, School of Psychology, University of New South Wales; Lee Averell and Scott Brown, School of Psychology, University of Newcastle.

Correspondence concerning this article should be addressed to Babette Rae, School of Psychology, University of Newcastle, Callaghan NSW 2308, Australia. E-mail: [rae.babette@gmail.com](mailto:rae.babette@gmail.com)

2010, 2011). This result exemplifies “selective influence,” the idea that changes in a particular cognitive process (e.g., older adults are more cautious) are captured in the model by changes in just one model parameter (the threshold). Other examples of applied implications include workload capacity (Eidels, Donkin, Brown, & Heathcote, 2010), alcohol use (van Ravenzwaaij, Dutilh, & Wagenmakers, 2012), sleep deprivation (Ratcliff & Van Dongen, 2011), and consumer choice (Hawkins et al., in press).

Selective influence is not just a useful property for data analysis, it has also been used as a test of the models themselves. For example, Ratcliff and Rouder (1998) found that a manipulation of stimulus difficulty selectively influenced drift rates while a caution manipulation selectively influenced thresholds, and they interpreted this as evidence in favor of their model. There have been numerous other reports of selective influence. Ho, Brown, and Serences (2009) found that changes in the response modality were captured by their model’s nondecision time parameter. Voss, Rothermund, and Voss (2004) reported a sequence of experiments that confirmed selective influence of several different experimental manipulations on key components of the diffusion model.

Following Ratcliff and Rouder’s (1998) precedent, Usher and McClelland (2001) and Brown and Heathcote (2005, 2008) took pains to establish that their new theories of decision making provided the same account of selective influence as the diffusion model. Thus, one initial benchmark test used to judge new models was the demonstration that caution manipulations selectively influenced threshold parameters. The usefulness of this test was supported by dozens of different applied studies that reported successful fits to data from experimental manipulations of decision caution through selective changes in only the models’ threshold parameters (e.g., Forstmann et al., 2011; Hawkins, Brown, Steyvers, & Wagenmakers, 2012; Ratcliff & Rouder, 1998; Ratcliff et al., 2007; Starns & Ratcliff, 2010; Usher & McClelland, 2001; Wagenmakers, Ratcliff, Gomez, & McKoon, 2008).

However, in amongst the many studies that report selective influence of caution manipulations on decision thresholds, there have been hints that something more complex might be afoot. Vanderkerckhove, Tuerlinckx, and Lee (2008) replicated Ratcliff and Rouder’s (1998) analyses in a Bayesian framework and reached quite a different conclusion, that the manipulation of caution was best described in the diffusion model by changes in both threshold and drift rate. Heathcote and Love (2012) identified a similar result in their LBA analysis of lexical decision data collected by Wagenmakers et al. (2008). Starns, Ratcliff, and McKoon (2012, pp. 14–15) found similar evidence in favor of the idea that drift rates are improved under accuracy emphasis.

Our aim here was to carefully test the selective influence assumption about caution in a variety of experimental paradigms. This test is important for both theoretical and practical reasons. From a theoretical viewpoint, the assumption of selective influence has become a yardstick with which to judge new theories. If the assumption is unwarranted, then we may have been misguided before. From a practical viewpoint, evidence accumulation models are used frequently to understand decision making in domains from consumer choice to short-term memory, from the effects of alcohol to sleep deprivation and depression. If the assumption of selective influence has been wrongly applied, it is possible that we have been misled in some of these analyses.

Previous support for the assumption that response caution selectively influences decision threshold has been drawn from studies in which data were analyzed under an a priori assumption of selective influence. Support for the assumption was then inferred from the ability of the model to adequately fit the data. This approach ignores the question of whether a different model—one that does not assume selective influence—might provide much better agreement with the data. We report an experiment that manipulates caution via instructions that either emphasize the speed or accuracy of responding. This experiment provides the basis for a set of converging model-based tests, and a model-free test. Our model-based analyses begin by identifying relatively unconstrained versions of the diffusion and LBA models that provide an accurate account of the major trends in the distribution of response times (RT) for correct and incorrect choices. One model-based test compares drift rate parameter estimates to determine whether they differ significantly between speed and accuracy emphasis conditions.

Further, four model-based tests compared the least constrained models to models that impose the selective influence assumption by constraining the different emphasis conditions to share the same drift rate estimates (“constrained models”). Because they are less flexible, the constrained models necessarily have greater misfit than the least constrained models. We examine the constrained model graphically to see if they miss any major trends in our data and use the  $\chi^2$  distributed deviance measure to test whether the increase in misfit is statistically reliable. We also compared constrained and unconstrained models using Bayesian information criterion (BIC) and Akaike information criterion (AIC; Myung & Pitt, 1997). These measures balance goodness-of-fit against complexity, quantified by the number of free parameters. Due to the way it quantifies complexity, and for data sets of the size we consider, BIC tends to select simpler models with fewer parameters than does AIC. Even so, the results of BIC and AIC mostly agree in the analyses below. When they do not agree, the interested reader should refer to Wagenmakers and Farrell (2004, p. 194–195) for a comparison (see also Burnham & Anderson, 2002, and Kass & Raftery, 1995).

Our model-free test was based on response deadline trials, in which a signal prompted participants to make immediate choices. Meyer, Irwin, Osman, and Kounios (1988) used response deadlines to examine the accumulation of evidence before a regular (i.e., participant-initiated) decision would have been made. Response deadline procedures have a long history in the study of decision-making models (McElree & Doshier, 1989; Wickelgren, 1977). Meyer et al.’s procedure randomly intermixes deadline trials with regular decision-making trials. We used their paradigm to look for differences in evidence accumulation speed between different caution conditions.

If caution affects only the threshold (the selective influence assumption), processing should be identical in the speed-emphasis and accuracy-emphasis conditions prior to a decision threshold being reached. Hence the accuracy of deadline responses made before the threshold is crossed should be unaffected by caution. Alternatively, if caution affects the information extracted from the stimulus (i.e., drift rate), cognitive processing will differ from stimulus onset, and the accuracy of deadline responses will differ with caution. Although deadline accuracy has the potential to provide model-free evidence, in practice that evidence can be

confounded by decision processes that reach threshold before the response signal (Ratcliff, 1988, 2006). To address this problem we also performed a model-based analysis on the deadline data.

## Method

### Participants

Forty-nine participants were recruited from a first year psychology pool and from the general university population. Participants were reimbursed at a rate of \$15 per hour or given course credit. Data from 15 participants were rejected because more than 10% of their responses were faster than 0.18 s or slower than 1.5 s. Although rejecting 15 participants from 49 is a higher exclusion rate than for other cognitive experiments, the random-deadline task we used is very demanding on participants. For example, when developing this task, Meyer et al. (1988) found it necessary to train their participants for 6 hr before data collection.

### Stimuli

Stimuli were  $64 \times 64$  pixel ( $2.5 \text{ cm} \times 2.5 \text{ cm}$ ) patches, similar to those used by Ratcliff and Rouder (1998). Each pixel was either black or white. There were two categories of stimuli: Pixels in *light* squares had a 53% probability of being white, and pixels in a *dark* square had a 47% chance of being white. Presentation of stimuli on a computer screen was made dynamic by repeatedly cycling through four squares, chosen at random from a pregenerated set of 50 squares from each category. Cycling occurred at a rate of 0.015 s per square, and continued until a response was made.

### Procedure

On each trial, participants had to choose whether the stimulus was predominately light or dark, by pressing D or L on the keyboard, respectively. A randomly selected 20% of trials included a response signal; the appearance of red asterisks above and below the stimulus signaled the need to respond immediately. Asterisks on the response signal trials appeared at lags of 0.04 s, 0.12 s, 0.2 s, 0.25 s, 0.3 s or 0.4 s after the presentation of the stimulus. Participants were instructed to respond within 0.3 s of the presentation of the asterisks. On the remaining 80% of trials, participants had up to 5 s to respond.

The caution manipulation occurred in alternating blocks of trials, beginning with accuracy emphasis in the first block. At the beginning of accuracy-emphasis blocks "RESPOND ACCURATELY" appeared on the screen until participants pressed the space bar. In speed-emphasis blocks, "RESPOND QUICKLY" appeared in the same manner. In the accuracy-emphasis condition, feedback was given for correct or incorrect responses: "CORRECT" (in green font) or "INCORRECT" (in red font), respectively. In the speed-emphasis condition, in addition to the accuracy feedback, feedback was also given on response time. In regular decision trials, if response time was slower than 0.5 s, "TOO SLOW" appeared on the screen. In response deadline trials, if the response time was more than 0.3 s after the appearance of the asterisks, the feedback "BAD TIME" was given, while if the response was within 0.3 s the feedback "GOOD TIME" was given.

To improve compliance with the difficult procedure, we used a part-task training method. Participants began by practicing regular trials for approximately 30 min. Response deadline trials were then introduced in a 15 min practice period, where only the three slowest lags were used. The main test phase followed, with 20 participants completing one 1-hr session and the remaining 29 participants completing two 1-hr sessions within a 3-day period. There were 14 blocks of 104 trials in each 1-hr session.

## Results

### Data From Free Response Trials

We fit the specific versions of the diffusion and LBA models described by Heathcote and Love (2012) and Ratcliff and Tuerlinckx (2002), respectively. The models were fit to data from regular trials, with RTs outside the range 0.18 s to 1.5 s censored. The diffusion model was fit via quantile maximum probability estimation (Heathcote & Brown, 2004; Heathcote, Brown, & Mewhort, 2002) based on the 10th, 30th, 50th, 70th and 90th quantiles of correct and error responses in each experimental condition, while the LBA was fit via maximum-likelihood estimation. Quantile-based methods are standard practice for the diffusion model, for practical computational reasons.

We use the same symbols to refer to nondecision time parameters and drift rate parameters shared by the diffusion and LBA models. For both models  $t_{er} \sim t_0 + U(0, s_{t0})$ , that is, nondecision time is uniformly distributed between  $t_0$  and  $t_0 + s_{t0}$ . In the LBA model, evidence accumulation is deterministic, with a rate that varies from trial-to-trial according to a normal distribution with mean  $v$  and standard deviation  $s_v$ . In the diffusion model, these same two parameters ( $v$  and  $s_v$ ) specify a normal distribution that gives rise to a random sample of drift rate for each trial. Within each trial, evidence accumulates on average at the speed given by the drift rate sample, but there is also random variability from moment to moment. This moment to moment variability is the original "random walk" element of the model, and its standard deviation was fixed arbitrarily at 0.1, following convention.

Since the diffusion and LBA models differ in their accumulator structure, we use different symbols to reference those elements. For the diffusion model,  $a$  represents the distance between the thresholds. The starting point for accumulation, sometimes denoted  $z$ , was estimated by its relative position between the thresholds, denoted  $Z = z/a$ . Both models assume uniformly distributed variability in the accumulation starting point. For the diffusion model we assumed the variability in start point was centered on  $z$ , and we again estimated it as a proportion, in this case of the shorter of the distances from  $z$  to a threshold,  $SZ = \min(z, a-z)/a$ . For the LBA the start-points are uniformly distributed between zero and an upper bound denoted  $A$ . The distance from  $A$  to the threshold is  $B$ .

We used Donkin, Brown, and Heathcote's (2011) method to generate versions of the diffusion and LBA models that differed in how the different experimental manipulations influenced model parameters. The experimental manipulations in question were represented by a caution emphasis factor (speed vs. accuracy emphasis, denoted  $E$ ), and stimulus factor (dark vs. light stimulus, denoted  $S$ ). For the LBA we allowed for differences between accumulators corresponding to dark vs. light responses in the  $A$  and  $B$  parameters. This response factor (denoted  $R$ ) allows the



LBA to capture effects such as response bias (e.g., a bias to respond light by having a lower threshold,  $B$ , for the light accumulator). Effects of the response factor on  $A$  and  $B$  LBA parameters are analogous, respectively, to the  $Z$  and  $SZ$  factors in the diffusion model. In the LBA we also allowed for differences in drift rate parameters due to the match between a stimulus and an accumulator. For example, the mean drift rate for a bright stimulus will be higher for the bright (i.e., matching) accumulator than the dark (i.e., mismatching) accumulator. Changing parameter values across the match factor (denoted  $M$ ) allows the LBA to capture the effect of the stimulus on accuracy depending on the difference between the “matching” drift rate and the “mismatching” drift rate. In the diffusion model there is no corresponding factor, as the diffusion drift rate is analogous to the *difference* between matching and mismatching LBA drift rates.

Tables 1 and 2 denote different diffusion and LBA model versions by indicating the factors that affect each parameter, with an entry of “—” indicating a common value was estimated for all conditions. Where a parameter might be influenced by more than one factor we fit all possible orders of interactions among the factors as well as main effects. The least constrained (most complex) models that we fit are shown in the top row of each table. We made the conventional assumption that  $s_v = 1$  for the LBA. For both models we instantiated the notion of selective influence in the most lenient sense possible: The assumption of selective influence was operationalized as the assumption that drift rate parameters—and only drift rate parameters—were not influenced by the response caution factor ( $E$ ). For both models we also estimated a contamination probability parameter,  $p$ , for the proportion of trials on which participants made an unbiased guess with an RT that was uniformly distributed over the range from the fastest RT that was not censored (0.18 s) to the longest RT that was not censored (1.5 s).<sup>1</sup> Estimates of  $p$  were allowed to differ between speed and accuracy emphasis conditions.

For the diffusion model, we fit all models from the most complex to the least complex (where all parameters were equal across all conditions), resulting in 1,023 models to be analyzed for each participant’s data. For the LBA model, there were 255 models per participant, because we did not consider variants in which the  $M$  factor was dropped (without this, the model is forced to predict chance accuracy). Model variants were fit starting from the simplest, with the best fits of simpler models providing starting points for fits of more complex models.

Tables 1 and 2 show the results of the model fitting for the diffusion and LBA models, respectively. For example, the second entry on the top row of Table 1 reads “E,S,” which means that the drift rate parameter (see column heading, “ $v$ ”) was influenced by factors  $E$  and  $S$ , in this particular model variant (the least constrained model—see row label). The least constrained variants of the models (top rows in Tables 1 and 2) naturally fit the data best, but these models did not provide the best descriptions of the data because of their complexity, as shown by their higher BIC and AIC values. We divided the model variants into those that respected the selective influence assumption (i.e., no effect of speed vs. accuracy emphasis on drift rate parameters) and those that did not. Both BIC and AIC indicated that the best models for these data were models that did *not* respect the selective influence assumption. That is, the models with the best (smallest) AIC and BIC values in Tables 1 and 2 all include an effect of speed vs. accuracy emphasis (factor

$E$ ) on the drift rate parameter ( $v$ ). This effect was quite pronounced. The best of the models that respected the selective influence assumption, shown in the lower halves of Tables 1 and 2, always had much poorer BIC and AIC values, with differences of more than 166 in all cases.

Tables 1 and 2 do not allow direct comparison of the goodness-of-fit of the diffusion versus LBA models. This is because the deviance, AIC, and BIC values are based on maximum likelihood values for the LBA model, but quantile-based pseudolikelihoods for the diffusion model (see Speckman & Rouder, 2004, for a discussion). To provide some comparison, we calculated, for each participant, likelihood ratio  $G^2$  measures of misfit based on the observed ( $O$ ) and predicted ( $E$ ) frequencies of responses between the quantiles:  $2 \sum_i O_i \ln(O_i/E_i)$ . Consistent with the slightly better fit for the LBA than diffusion evident in Figures 1 and 2, misfit summed over participants for the LBA ( $G^2 = 5,469$ ) was less than for diffusion ( $G^2 = 6,238$ ). Similar results were obtained for Pearson’s  $\chi^2$ .

Figures 1 and 2 illustrate the differences between the models in accounting for the data, for the diffusion and LBA models, respectively. All variants of both models adequately account for RT distributions (center and right column in each figure), but imposing the selective influence assumption causes a clear misfit for decision accuracy (left column). Even though the fit to the RT distributions is generally quite good, there is a tendency for both models to predict a greater degree of skew than observed in RT for incorrect responses, although for the LBA this is only the case under accuracy emphasis.

We confirmed that imposing the selective influence assumption caused a statistically reliable decrease in goodness of fit by applying a  $\chi^2$  test to the difference in fit between the two nested models. This test indicated that the increase in misfit was highly significant for both the diffusion model,  $\chi^2(136) = 500$ ,  $p < .001$ , and the LBA model,  $\chi^2(136) = 848$ ,  $p < .001$ . Note that for the diffusion model this test is approximate because of the quantile estimation method (see Speckman & Rouder, 2004), but it nevertheless provides converging evidence with the AIC and BIC model selection methods.

The bottom rows of Figures 1 and 2 show the fits of the least constrained models that assume a selective influence of caution (i.e., the “Selective Caution Effect” models in Tables 1 and 2). Imposing the selective influence assumption on the effect of caution has little effect on the quality of fits to RT distribution. However, the selective influence assumption causes both models to clearly underestimate the difference in accuracy between speed emphasis and accuracy emphasis conditions, particularly for the LBA.

<sup>1</sup> Ratcliff and Tuerlinckx (2002) modeled contamination in a similar manner but assumed that the accuracy of contaminated trials equalled that of noncontaminated trials. We assume chance accuracy because this seemed more consistent with the idea that contaminated responses produced by a different process than uncontaminated responses. We found a low and equal overall level of contamination with the most flexible versions of both diffusion and LBA models that we fit (1.8%). However, some participants had appreciably higher levels; in particular both models estimated 13% contamination on average for one participant. Higher contamination likely reflects the difficult nature of the task and some carry-over effects from deadline to regular trials.

Table 1  
*Diffusion Model Results*

Variant	<i>a</i>	<i>v</i>	<i>sv</i>	<i>Z</i>	<i>SZ</i>	<i>t</i> <sub>0</sub>	<i>st</i> <sub>0</sub>	<i>p</i>	<i>k</i>	D	AIC	BIC
Least Constrained	E	E, S	E, S	E	E	E	E	E	20	0	1,360	5,030
AIC Selected	E	E, S	S	—	E	E	E	—	16	102	1,190	4,126
BIC Selected	E	E, S	—	—	—	E	—	—	13	545	1,430	3,815
Selective Caution Effect	E	S	S	E	E	E	E	E	16	500	1,588	4,524
AIC Selected	E	S	S	E	—	E	E	E	15	512	1,532	4,285
BIC Selected	E	S	—	E	—	E	—	—	12	963	1,780	3,981

*Note.* *a* = the distance between the thresholds; *v* = mean drift rate; *sv* = standard deviation of drift rate; *Z* = the starting point for accumulation that was estimated by its relative position between the thresholds; *SZ* = an estimated proportion of the shorter of the distances from *z* (the center of the start point variability) to threshold; *t*<sub>0</sub> = the lower bound of the uniformly distributed non-decision time; *st*<sub>0</sub> = the width of the uniformly distributed nondecision time; *p* = a contamination probability parameter, for the proportion of trials on which participants made an unbiased guess with a response time that was uniformly distributed over the noncensoring range; *k* = number of model parameters; E = speed versus accuracy emphasis; S = dark versus light stimulus manipulation; D = deviance; AIC = Akaike information criterion; BIC = Bayesian information criterion. D, AIC, and BIC were calculated by summing deviance and the number of model parameters (*k*) for fits to individual participants and the number of data points per participant over participants. Values for these statistics in the table have the deviance for the least constrained model subtracted and cannot be compared between Tables 1 and 2 because of differences in calculation (see text). The AIC and BIC selected models have minimum AIC and BIC values within the full set of models (rows 2 and 3) or within the set of models where caution does not influence drift rate parameters (rows 5 and 6). Table entries of E and S describe which factors influenced each parameter, and em dashes signify parameters that were constant across all factors.

Another way to investigate the selective influence assumption is to compare drift rate parameters estimated from the speed-emphasis and accuracy-emphasis conditions, which are shown in Table 3, for the least constrained model fits. For the LBA, mean drift rates (*v*) were higher when there was a match between the stimulus and response than when there was a mismatch,  $F(1, 33) = 91, p < .001$ . Contrary to the assumption of selective influence, this difference was larger under accuracy emphasis than speed emphasis, interaction  $F(1, 33) = 29.7, p < .001$ . The same was true for the diffusion model, with higher mean drift rates under accuracy emphasis than speed emphasis,  $F(1, 33) = 17.4, p < .001$ . This interacted with stimulus type,  $F(1, 33) = 11.2, p < .005$ , due to a larger emphasis effect for dark than light stimuli. The diffusion rate variability parameter (*s<sub>v</sub>*) was fairly constant across conditions with no effects approaching significance (*ps* > .4).

### Data From Response Signal Trials

To reduce contamination by trials on which participants ignored the response signal, we limited our analyses to those trials in which responses occurred more than 0.05 s but less than 0.18 s after the signal (similar rules have been used previously by Meyer et al., 1988, and Ratcliff, 1988). By this criterion the shortest stimulus-to-signal lag manipulation (0.04 s) failed; only 3.1% of 0.04-s response signal trials were followed by a response within the acceptable window, so we excluded the 0.04-s deadline data from further analysis. The open and filled circles in Figure 3 show the proportion of correct responses as a function of the signal lag separately for the speed emphasis and accuracy emphasis conditions, respectively. Note that the data are the same in all four panels—only the model fits differ.

Table 2  
*LBA Model Results*

Variant	<i>B</i>	<i>A</i>	<i>v</i>	<i>t</i> <sub>0</sub>	<i>p</i>	<i>k</i>	D	AIC	BIC
Least Constrained	E, R	E, R	E, S, M	E	E	21	0	1,428	7,835
AIC Selected	R	E, R	E, S, M	E	E	19	82	1,374	7,170
BIC Selected	R	R	E, M	E	—	12	1,193	2,009	5,670
Selective Caution Effect	E, R	E, R	S, M	E	E	17	848	2,004	7,190
AIC Selected	E, R	E, R	S, M	E	E	17	848	2,004	7,190
BIC Selected	E	E, R	M	—	E	12	1,646	2,462	6,122

*Note.* LBA = linear ballistic accumulator; *B* = the distance from the upper bound of the start-point distribution (which begins at zero) to the threshold; *A* = the upper bound of the start-point distribution (which begins at zero); *v* = mean drift rate; *t*<sub>0</sub> = the lower bound of the uniformly distributed nondecision time; *st*<sub>0</sub> = the width of the uniformly distributed nondecision time; *p* = a contamination probability parameter, for the proportion of trials on which participants made an unbiased guess with a response time that was uniformly distributed over the noncensoring range; *k* = number of model parameters; D = deviance; AIC = Akaike information criterion; BIC = Bayesian information criterion; E = the parameter changes with speed versus accuracy emphasis; R = the parameter changes between the dark and light response accumulators; S = the parameter changes between dark versus light stimuli; M = the parameter takes on one value for accumulators whose response matches the stimulus and a different value for accumulators whose response fails to match the stimulus. D, AIC, and BIC were calculated by summing deviance and the number of model parameters (*k*) for fits to individual participants and the number of data points per participant over participants. Values for these statistics in the table have the deviance for the least constrained model subtracted and cannot be compared between Tables 1 and 2 because of differences in calculation (see text). The AIC and BIC selected models have minimum AIC and BIC values within the full set of models (rows 2 and 3), or within the set of model where caution does not influence drift rate parameters (rows 5 and 6). Table entries of E, S, R, M describe which factors influenced each parameter, and em dashes signify parameters that were constant across all factors.

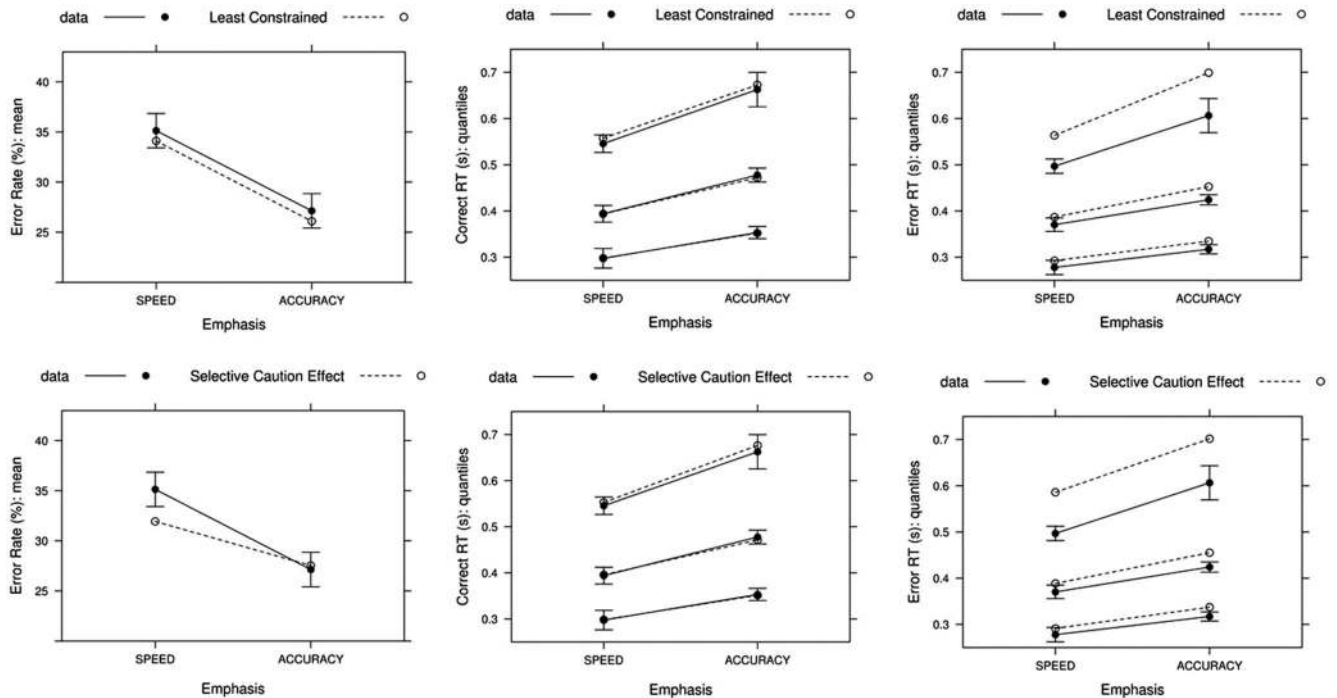


Figure 1. Diffusion model fits. Decision accuracy (left column) and response time (RT) distributions for correct (middle column) and error responses (right column). For RT distributions, the lines from bottom to top correspond to 10th, 50th and 90th percentiles. In all panels, the data are shown by solid lines and symbols and diffusion model fits by open symbols and dotted lines. Data points are accompanied by 95% within-subject confidence intervals (Morey, 2008). The top row shows fits of the “Least Constrained” model specified in Table 1. The bottom row shows fits of the “Selective Caution Effect” model specified in Table 1.

For 0.12-s and 0.2-s signal lags, the proportion of correct responses was not significantly above chance and was not significantly different between speed-emphasis and accuracy emphasis-conditions. However, for the slowest three signal lags, the proportion of correct responses was greater in the accuracy-emphasis condition than the speed-emphasis condition, according to repeated measures  $t$  tests ( $p < .01$  for 0.25-s and 0.3-s lags, and  $p < .05$  for the 0.4-s lag). The differences in the proportion of correct responses at later response signal lags between the speed-emphasis and accuracy emphasis conditions suggest that the assumption of selective influence does not hold in these data. Instead it implies that, in agreement with the results for regular trials reported above, drift rates are improved in the accuracy-emphasis condition compared with the speed-emphasis condition.

Ratcliff (1988, 2006) demonstrated that the interpretation of response deadline data can depend on whether the fastest decision processes terminate (i.e., reached a threshold) before the response signal. To test this idea in our data, we analyzed the deadline data, using assumptions similar to Ratcliff’s, using diffusion and LBA model fits from the regular, free response trials. This provides a strong test of the models, similar to cross-validation methods, by requiring them to accommodate data from some conditions using parameters estimated from different conditions (see Bussemeyer & Wang, 2000, for a general treatment of this approach as a model-selection method).

The model fits from the regular, free-response trials allowed the models to predict both the probability of a decision being reached

prior to a response signal and the probability of those early decisions being correct. Combined with the assumption that responses on the remaining signal trials were uninformed guesses, with 50% accuracy, this enabled us to generate model predictions for accuracy on deadline trials. We estimated one new free parameter for the response signal trials: a perceptual delay reflecting the time taken to notice the response signal ( $t_{er,signal}$ ). Estimates of the perceptual delay averaged across participants were 0.064 s and 0.062 s for the least constrained selective caution effect diffusion models. Corresponding LBA estimates were 0.04 s and 0.057 s, respectively.

The solid and dashed lines in Figure 3 show the model predictions. The upper panels show predictions from the diffusion model, and the lower panel shows predictions from the LBA model. For each model, the left-hand panels show predictions from the least constrained model that imposes the selective caution effect assumption, and the right-hand panels show predictions based on parameters from the best model chosen by BIC from all models fit. All models fit well for the 0.2-s and 0.4-s lags. However, despite the BIC selected models using fewer parameters (see Tables 1 & 2), they provide a much better fit at the 0.25-s and 0.3-s lags. Recall that, for both the diffusion and LBA, BIC selected models allowed caution to influence drift rates, so a greater proportion of responses are correct at these shorter lags under accuracy emphasis because the higher drift rates have allowed more information to accrue. When caution is not allowed to influence drift rates accuracy is underpredicted at these shorter lags, but greater accuracy

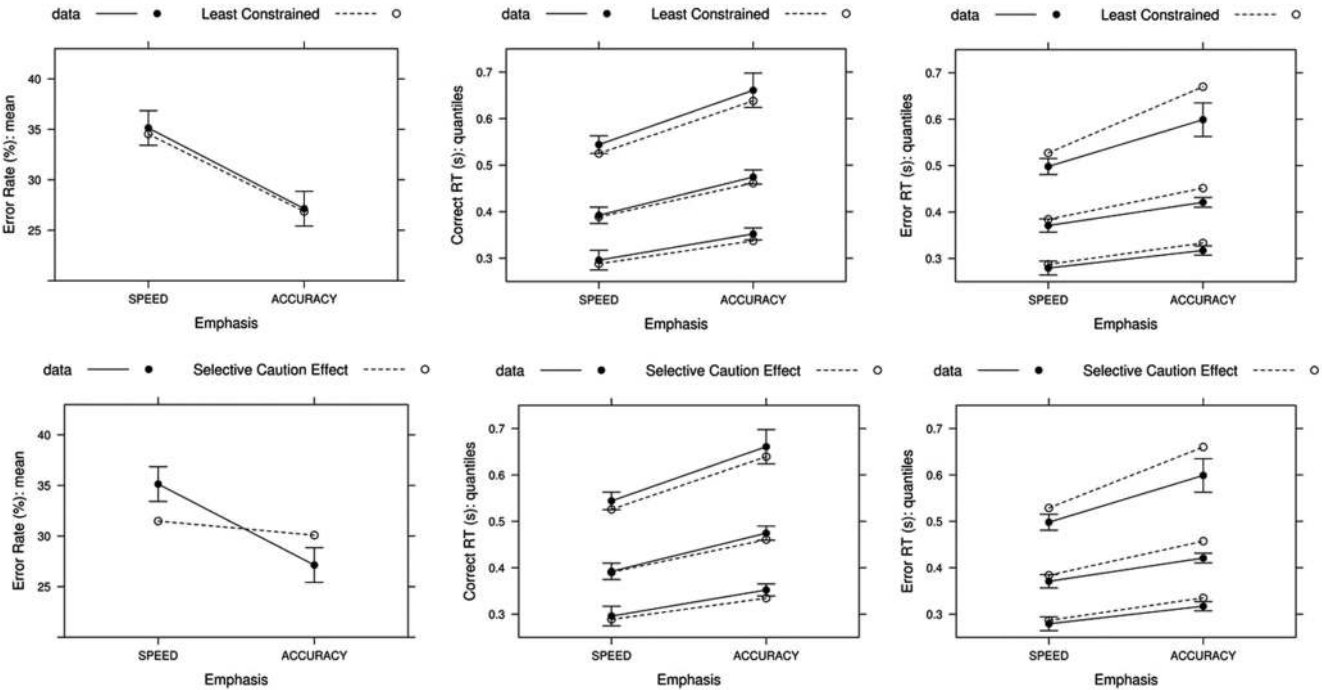


Figure 2. Linear ballistic accumulator (LBA) model fits. Decision accuracy (left column) and response time (RT) distributions for correct (middle column) and error responses (right column). For RT distributions, the lines from bottom to top correspond to 10th, 50th and 90th percentiles. In all panels, the data are shown by solid lines and symbols and LBA model fits by open symbols and dotted lines. Data points are accompanied by 95% with-subject confidence intervals (Morey, 2008). The top row shows fits of the “Least Constrained” model specified in Table 1. The bottom row shows fits of the “Selective Caution Effect” model specified in Table 2.

can be accommodated at the longest lag because enough time has passed for a sufficient proportion of early-terminating decisions (with greater than chance accuracy) to occur. As a final check, we repeated the model-based analyses allowing the responses on the unfinished trials to be “informed” guesses, for which the response issued reflects the current state of the evidence accumulation process. As also observed by Ratcliff (1988), this made little difference to the results.

The models predict increasing response accuracy on the signal trials with increasing signal lag. However, at very long lags (beyond those used in our experiment) the models actually predict decreasing response accuracy. This occurs because very long sig-

nal lags lead to a situation in which almost all responses are made before the signal. The only trials in which responses will be observed after the signal (within the acceptable window) are those for which the particular drift rate samples are very weak, leading to very slow responses with close to chance level accuracy.

### The Effect of Emphasizing Decision Speed on Lexical Evidence

The brightness discrimination experiment above showed that emphasizing decision speed changes the evidence derived from perceptual processes but is this also true when the evidence is derived from cognitive processes? We investigated this question in linguistic processing by applying our analyses of regular (free response) trials to lexical decision task data reported by Wagenmakers et al. (2008, their Experiment 1). These analyses also test the possibility that our results are specific to the particular speed–accuracy tradeoff instructions we employed, or to situations in which accuracy is relatively low as it was in our experiment (around 70%). In contrast, Wagenmakers et al. reported accuracy above 90% in many conditions. They manipulated speed- vs. accuracy-emphasis factorially with a four-level stimulus-type factor (S), made up of three types of words: very-low frequency (vlf), low frequency (lf) and high frequency (hf) and nonwords (nw). Heathcote and Love (2012) report fits of the LBA model to these data and observed a clear failure of selective influence; a model with drift rate parameters fixed over emphasis conditions could not

Table 3  
Drift Rate Parameter Estimates From the Least Constrained Diffusion and LBA Models

Model	Parameter	Speed emphasis		Accuracy emphasis	
		Dark	Light	Dark	Light
Diffusion	$\nu$	0.132	0.188	0.217	0.212
Diffusion	$s_\nu$	0.093	0.078	0.093	0.061
LBA	$\nu$ (match)	3.29	3.56	3.65	3.84
LBA	$\nu$ (mismatch)	2.18	2.07	1.46	1.46

Note. LBA = linear ballistic accumulator;  $\nu$  = mean drift rate;  $s_\nu$  = standard deviation of drift rate.



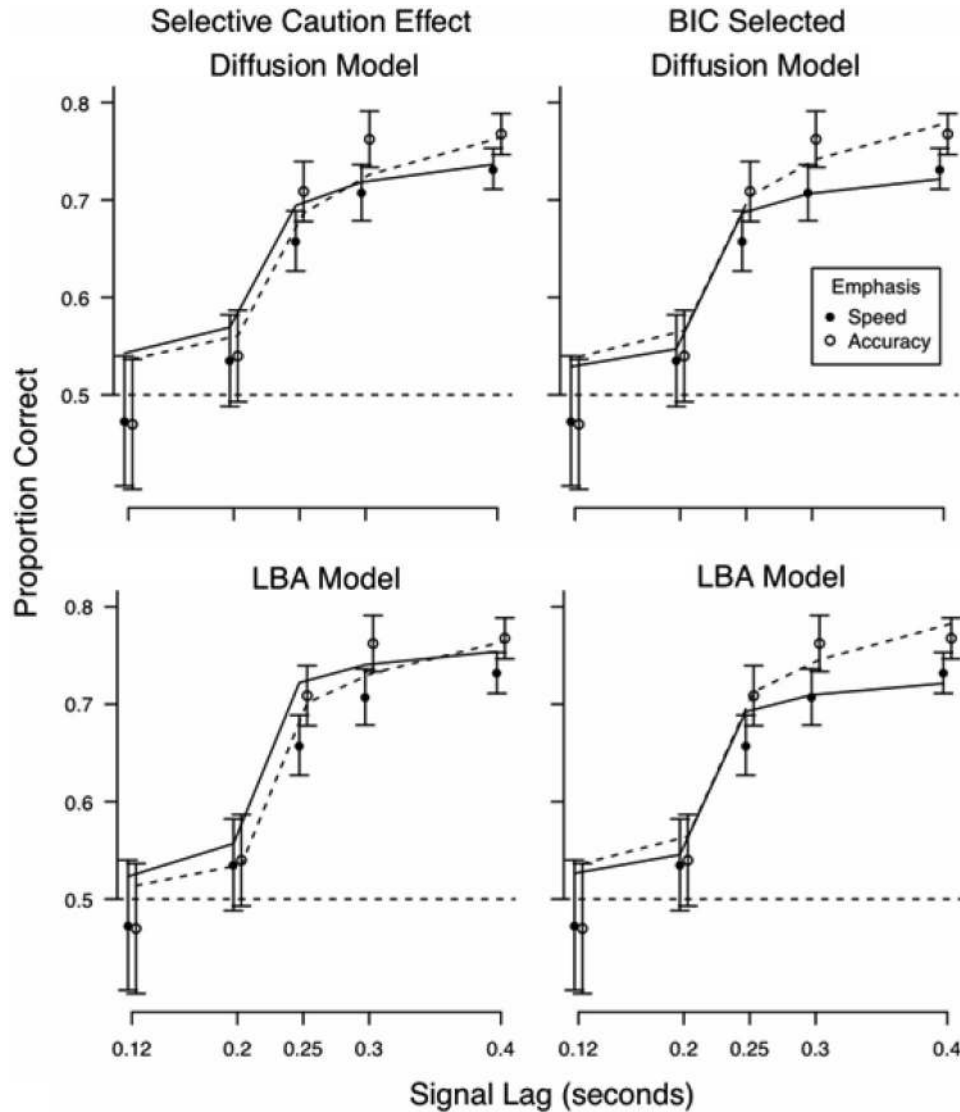


Figure 3. Proportion of correct responses as a function of the signal lag for speed emphasis and accuracy emphasis in data (symbols), and corresponding predictions for the Diffusion and linear ballistic accumulator (LBA) models (lines). Error bars represent one standard error, calculated on a within-subject basis, for the comparison between speed- versus accuracy-emphasis (Morey, 2008). The  $x$ -axis positions of the speed- and accuracy-emphasis data are offset slightly, for clarity only.

account the effect of instructions on accuracy (this model fit is shown in the lower panels of Figure 4). The top panels in Figure 4 show model fits, also reported by Heathcote and Love, in which drift rate parameters were allowed to vary with emphasis, resulting in much better fits to data. Confirming the impression from Figure 4, both BIC and AIC model selection supported an emphasis effect on variability in drift rates ( $sv$ ; see Heathcote & Love's Table 1). Hence, we conclude that the LBA model supports the conclusion that emphasizing decision speed can influence the evidence derived from linguistic processes.

To investigate whether the diffusion model supports the same conclusions as the LBA model for Wagenmakers et al.'s (2008) data, we used the same free-response-data fitting methods as with

our perceptual data, with one exception. In preliminary investigations we found little evidence of contamination and so we report fits with only a single estimated contamination probability parameter ( $p$ ), rather than allowing separate estimates for each speed and accuracy emphasis condition: estimates of the contamination proportion were less than 1% on average.

Table 4 reports model selection results similarly to Tables 1 and 2. As always, the least constrained model (top row) had the best fit to data (deviance) but did not provide the most parsimonious description of the data, as shown by BIC and AIC. According to AIC, the best model for these data was one that did not respect the selective influence assumption. However, BIC did select a model that respected the selective influence assumption. To further in-



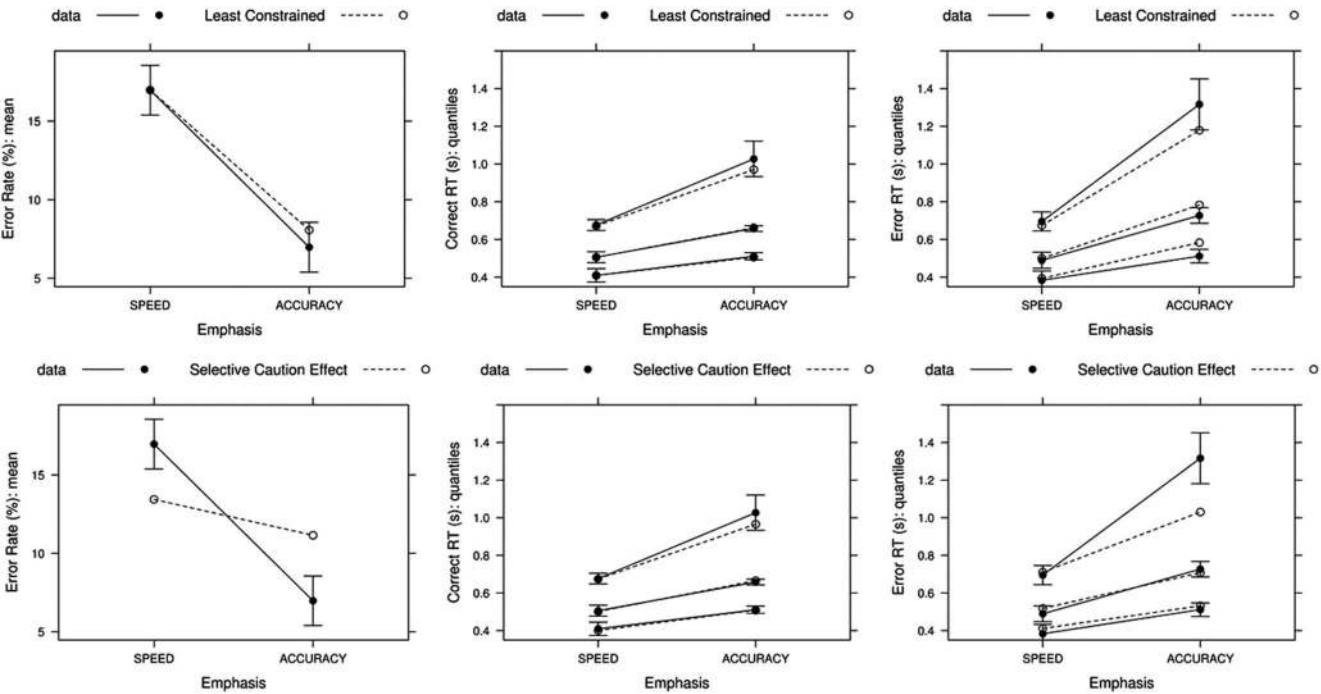


Figure 4. Linear ballistic accumulator (LBA) model fits to Wagenmakers et al.'s (2008) data. Response accuracy (left column), and response time (RT) distributions for correct responses (middle column) and error responses (right column). For RT distributions, the lines from bottom to top correspond to 10th, 50th and 90th percentiles. In all panels, the data are shown by solid lines and symbols and LBA model fits by dotted lines and open symbol. Model fits are averaged over participants and stimulus conditions. Data points are accompanied by 95% with-subject confidence intervals (Morey, 2008). The top row shows fits of the “Least Constrained” model for which the E (speed emphasis) factor could affect drift rate parameters. (The top row fits come from Table 1 in Heathcote & Love, 2012). The bottom row shows fits of the “Selective Caution Effect” model that removes the effect of E on  $v$  and  $sv$  parameters.

investigate this tension, we once again compared the decrease in goodness of fit resulting from imposing the selective influence assumption, using nested model likelihood ratio tests against a  $\chi^2$  distribution. As before, the reduction in fit of the diffusion model

with the selective influence assumption was highly significant,  $\chi^2(136) = 237, p < .001$ .

Figure 5 shows goodness of fit of the diffusion model to the lexical decision data. As before, the key is in accommodating the

Table 4  
Diffusion Model Results for Fits to Wagenmakers et al.'s (2008) Data

Variant	$a$	$v$	$sv$	$Z$	$SZ$	$t_0$	$st_0$	$k$	D	AIC	BIC
Least Constrained	E	E, S	E, S	E	E	E	E	27	0	918	3,362
AIC Selected	E	E, S	S	E	E	E	E	23	66	848	2,930
BIC Selected	E	S	—	—	E	E	—	14	635	1,111	2,378
Selective Caution Effect	E	S	S	E	E	E	E	19	237	883	2,603
AIC Selected	E	S	S	E	—	E	E	19	237	883	2,603
BIC Selected	E	S	—	E	—	E	—	14	635	1,111	2,378

Note.  $a$  = the distance between the thresholds;  $v$  = mean drift rate;  $sv$  = standard deviation of drift rate;  $Z$  = the starting point for accumulation that was estimated by its relative position between the thresholds;  $SZ$  = an estimated proportion of the shorter of the distances from  $z$  (the center of the start point variability) to threshold;  $t_0$  = the lower bound of the uniformly distributed non-decision time;  $st_0$  = the width of the uniformly distributed nondecision time;  $p$  = a contamination probability parameter, for the proportion of trials on which participants made an unbiased guess with a response time that was uniformly distributed over the noncensoring range;  $k$  = number of model parameters; D = deviance; AIC = Akaike information criterion; BIC = Bayesian information criterion; E = speed versus accuracy emphasis; S = lexical stimulus manipulation with four levels (high, low and very low word frequency and nonwords). D, AIC, and BIC were calculated by summing deviance and the number of model parameters ( $k$ ) for fits to individual participants and the number of data points per participant over participants. Values for these statistics in the table have the deviance for the least constrained model subtracted. The AIC and BIC selected models have minimum AIC and BIC values within the full set of models (rows 2 and 3) or within the set of model where caution does not influence drift rate parameters (rows 5 and 6). Table entries of E and S describe which factors influenced each parameter, and em dashes signify parameters that were constant across all factors.

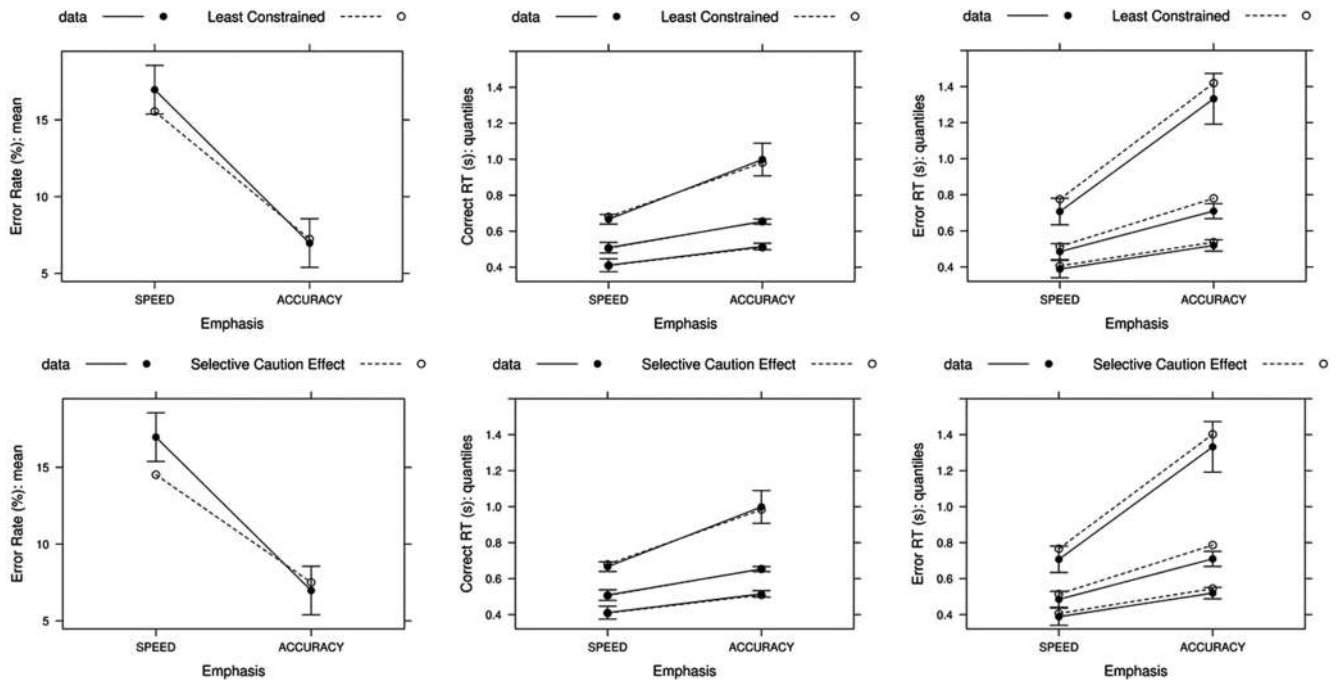


Figure 5. Diffusion model fits to Wagenmakers et al.'s (2008) data. Response accuracy (left column), and response time (RT) distributions for correct responses (middle column) and error responses (right column). For RT distributions, the lines from bottom to top correspond to 10th, 50th and 90th percentiles. In all panels, the data are shown by solid lines and symbols and diffusion model fits by dotted lines and open symbols. Model fits are averaged over participants and stimulus conditions. Data points are accompanied by 95% with-subject confidence intervals (Morey, 2008). The top row shows fits of the "Least Constrained" model specified in Table 4. The bottom row shows fits of the "Selective Caution Effect" model specified in Table 4.

difference in response accuracy between the speed and accuracy emphasis conditions (left panels). With the selective influence assumption imposed (lower row), the diffusion model does not accommodate this difference nearly as well as when the assumption is relaxed (upper row).

Table 5 contains the drift rate parameter estimates from the least constrained diffusion and LBA models. Although the main effect of emphasis on the rate ( $v$ ) parameter was not significant ( $F < 1$ ), a failure of selective influence was indicated by a significant

interaction between emphasis and stimulus type,  $F(3, 48) = 4.46$ ,  $\epsilon = .53$ ,  $p = .03$ . The interaction was caused by the effect of emphasis on drift rate being mostly confined to the most difficult low frequency stimuli; an analysis of variance restricted to estimates for these stimuli showed a significant main effect,  $F(1, 16) = 6.94$ ,  $p = .02$ . This interaction of selective influence with stimulus class may explain why BIC failed to pick an on-average effect of selective influence. Stronger effects were evident for the LBA model. The main effect of emphasis on mean drift rate ( $v$ )

Table 5

Drift Rate Parameter Estimates From the Least Constrained Diffusion and LBA Models Fit to Wagenmakers et al.'s (2008) Data

Model	Parameter	Emphasis	High frequency	Low frequency	Very-low frequency	Nonword
LBA	$v(\text{match})$	Accuracy	2.81	2.40	2.16	2.49
LBA	$v(\text{match})$	Speed	3.39	2.97	2.76	3.14
LBA	$v(\text{mismatch})$	Accuracy	0.19	0.27	0.36	0.12
LBA	$v(\text{mismatch})$	Speed	0.91	1.05	1.33	0.78
LBA	$sv(\text{match})$	Accuracy	0.69	0.67	0.73	0.73
LBA	$sv(\text{match})$	Speed	0.64	0.70	0.77	0.76
LBA	$sv(\text{mismatch})$	Accuracy	1.00	1.06	1.22	0.90
LBA	$sv(\text{mismatch})$	Speed	1.43	1.53	1.55	1.38
Diffusion	$v$	Accuracy	0.609	0.350	0.243	0.287
Diffusion	$v$	Speed	0.634	0.307	0.187	0.302
Diffusion	$s_v$	Accuracy	0.235	0.141	0.169	0.093
Diffusion	$s_v$	Speed	0.241	0.135	0.205	0.079

Note. LBA = linear ballistic accumulator;  $v$  = mean drift rate;  $sv$  = standard deviation of drift rate.

was significant for both the matching accumulator,  $F(1, 16) = 23.7, p < .001$ , and the mismatching accumulator,  $F(1, 16) = 15.9, p = .001$ . The main effect of emphasis on drift rate standard deviation was also significant for the mismatching accumulator,  $F(1, 16) = 24.8, p < .001$ , but it was the interaction with stimulus type that was significant for the matching accumulator,  $F(3, 16) = 4.78, \epsilon = .95, p = .006$ , with the drift rate for accuracy emphasis being greater than the drift rate for speed emphasis for the high frequency words, whereas the opposite was so for the other three types of stimuli.

The results of the LBA model analyses indicate a failure of the selective caution effect assumption for the lexical decision data. The results of the diffusion model analysis were less strong, but nevertheless there was some evidence that the selective influence assumption has to be abandoned in order to improve goodness of fit, particularly for the error rates. Although the failure of selective influence is less marked for the diffusion than LBA model—consistent with our results from the perceptual paradigm—even for the diffusion model the majority of the evidence rejects the selective caution effect assumption: Imposing selective influence clearly underestimates the error rate effect and is rejected by AIC model selection, and there are significant effects of emphasis on mean drift rate parameter estimates.

### The Effect of Emphasizing Decision Speed on Mnemonic Evidence

The brightness discrimination and lexical decision experiments showed that emphasizing decision speed changes the evidence derived from both perceptual and lexical processes, but does this extend to evidence derived from episodic memory? Our new experiment further tests the generality of our findings over different speed and accuracy emphasis instructions and in a third accuracy range (80% in our recognition memory task, compared with 70% in the perceptual experiment and 90% in lexical decisions).

## Method

### Participants

Forty-eight students from the University of Newcastle, Australia, participated in the experiment in return for course credit. One participant was excluded from further analysis due to very low accuracy, less than 55% overall. For the remaining 47 participants overall accuracy ranged from 63% to 93%.

### Stimuli

Stimuli consisted of 1,648 words with both frequency and concreteness ratings in the MRC psycholinguistic database (Coltheart, 1981). Of these words, 48 were used to construct a set of two study-test lists for practice, and the remainder to construct a set of 16 experimental study-test lists. Within the practice and experimental sets, words were allocated to lists and ordered randomly for each participant. In practice lists, 12 words were studied and 24 tested. In experimental lists, 56 words were studied and 100 tested. The first four and last four study words acted, respectively, as primacy and recency “buffers.” Two of the primacy and two of the recency buffers were randomly selected for testing, whereas all

of the remaining study words were tested. Responses to buffer words were not analyzed.

## Procedure

Testing took place in two 1-hr sessions on different days. The first session consisted of the two practice lists, one with speed and one with accuracy emphasis instructions and eight experimental lists. The second session used the other eight experimental lists. In each session speed and accuracy instructions were alternated between lists, with half of the participants beginning with speed and half with accuracy in session one, with the opposite order in session two. Participants were told that approximately half of the test words were studied on the last list (old words) and half not (new words).

Stimuli were presented on a computer screen and responses collected through the computer keyboard. Half of the participants responded old by pressing “z” key and new by pressing “/,” with the opposite assignment for the remaining participants. Words were studied one at a time, being present on the screen for 1 s, preceded and followed by blank screens for 0.15 s and 0.25 s. Following study, a screen informed the participants of the type of the next test (speed or accuracy). Each test word stayed on the screen until a response was made or 6 s elapsed, in which case “TIME LIMIT EXCEEDED! NO RESPONSE RECORDED!” was displayed. In speed blocks “TOO SLOW” was displayed after a response slower than 0.65 s and “TOO FAST” after a response faster than 0.25 s. In accuracy blocks “CORRECT” was displayed after correct responses and “INCORRECT” after incorrect responses.

## Results

As for the lexical decision data, preliminary investigations found little evidence of contamination: estimates of the contamination proportion 4% on average for diffusion and 1% for LBA. Thus, we report fits with only a single estimated contamination probability parameter ( $p$ ), rather than allowing separate estimates for each speed and accuracy emphasis condition. Tables 6 and 7 report model selection results for the diffusion and LBA models, respectively, using the same format as in earlier analyses. For the least constrained models of both types, speed vs. accuracy emphasis (E) was allowed to affect all parameters except rate variability ( $sv$ ). Allowing rate variability to vary with emphasis hardly improved fit and did not change model selection results but did lead to unstable parameter estimates for some participants, which is why we exclude those models. For the diffusion model, both drift rate parameters ( $v$  and  $sv$ ) were allowed to vary with stimulus (S, i.e., studied or old test words vs. unstudied or new test words). For the LBA model, threshold ( $B$ ) was allowed to vary with the response accumulator factor (R), and both drift rate parameters were allowed to vary with the stimulus-accumulator match (M) factor and mean drift rate ( $v$ ) was allowed to vary with the stimulus (S). Allowing  $sv$  to vary with the stimulus did not improve fit much or change model selection results and again led to unstable parameter estimates for some participants.

The top three rows of Tables 6 and 7 show that BIC and AIC both rejected the selective influence assumption for the diffusion and LBA models, respectively. The reduction in fit between the

Table 6  
Diffusion Model Results for Fits to Recognition Memory Data

Variant	<i>a</i>	<i>v</i>	<i>sv</i>	<i>Z</i>	<i>SZ</i>	<i>t<sub>0</sub></i>	<i>st<sub>0</sub></i>	<i>k</i>	D	AIC	BIC
Least Constrained	E	E, S	S	E	E	E	E	17	0	1,598	6,673
AIC Selected	E	E, S	S	E	E	E	E	17	0	1,598	6,673
BIC Selected	E	E, S	S	E	E	E	E	17	0	1,598	6,673
Selective Caution Effect	E	S	S	E	E	E	E	15	2,528	3,938	8,416
AIC Selected	E	S	S	E	E	E	E	15	2,528	3,938	8,416
BIC Selected	E	S	—	—	E	E	—	12	3,291	4,419	8,001

*Note.* *a* = the distance between the thresholds; *v* = mean drift rate; *sv* = standard deviation of drift rate; *Z* = the starting point for accumulation that was estimated by its relative position between the thresholds; *SZ* = an estimated proportion of the shorter of the distances from *z* (the center of the start point variability) to threshold; *t<sub>0</sub>* = the lower bound of the uniformly distributed non-decision time; *st<sub>0</sub>* = the width of the uniformly distributed nondecision time; *p* = a contamination probability parameter, for the proportion of trials on which participants made an unbiased guess with a response time that was uniformly distributed over the noncensoring range; *k* = number of model parameters; D = deviance; AIC = Akaike information criterion; BIC = Bayesian information criterion; E = speed versus accuracy emphasis; S = mnemonic stimulus manipulation with two levels (test item either previously studied or not). D, AIC, and BIC were calculated by summing deviance and the number of model parameters (*k*) for fits to individual participants and the number of data points per participant over participants. Values for these statistics in the table have the deviance for the least constrained model subtracted, and cannot be compared between Tables 6 and 7 due to differences in estimation procedures. The AIC and BIC selected models have minimum AIC and BIC values within the full set of models (rows 2 and 3) or within the set of model for which caution does not influence drift rate parameters (rows 5 and 6). Table entries of E and S describe which factors influenced each parameter, and em dashes signify parameters that were constant across all factors.

least constrained and selective influence models was also highly significant for both the diffusion model,  $\chi^2(94) = 2528$ ,  $p < .001$ , and the LBA model,  $\chi^2(94) = 1731$ ,  $p < .001$ .

Figures 6 and 7 show the goodness of fit of the diffusion and LBA models, respectively, to the recognition memory data. For both models, the fit of the least constrained model is quite accurate, except for slower error responses. Once again, the assumption of selective influence causes the models not to be able to fit the difference in response accuracy between the speed and accuracy emphasis conditions (left panels). With the selective influence assumption imposed (lower row), neither model can accommodate this difference as well as when the assumption is relaxed (upper row). Once again this failure is most marked for the diffusion model, although selective influence also causes problems in RT, for both slow correct responses in the speed condition and fast error responses in the accuracy condition.

Figures 6 and 7 show the goodness of fit of the diffusion and LBA models, respectively, to the recognition memory data. For

both models, the fit of the least constrained model is quite accurate, except for the slowest of the incorrect responses (top line in right panels). Once again, assuming selective influence causes the models to underestimate the difference in response accuracy between the speed and accuracy emphasis conditions (left panels). With the selective influence assumption imposed (lower row), neither model can accommodate this difference as well as when the assumption is relaxed (upper row). Once again this failure is most marked for the LBA model, although selective influence also causes problems in fits to error RTs for both models.

Table 8 shows the drift rate parameter estimates for least constrained diffusion and LBA models. There was a significant interaction between stimulus (new vs. old) and emphasis,  $F(1, 46) = 4.43$ ,  $p = .04$ , due to a significantly higher drift rate for new stimuli under accuracy than speed emphasis,  $F(1, 46) = 6.13$ ,  $p = .02$ , but no significant difference for old stimuli ( $F < 1$ ). For the LBA model there was a significant three-way interaction between stimulus, emphasis and match,  $F(1, 46) = 13.2$ ,  $p < .001$ . This

Table 7  
LBA Model Results for Fits to Recognition Memory Data

Variant	<i>B</i>	<i>A</i>	<i>v</i>	<i>sv</i>	<i>t<sub>0</sub></i>	<i>k</i>	D	AIC	BIC
Least Constrained	E, R	E	E, S, M	M	E	18	0	1,692	8,874
AIC Selected	E, R	E	E, S, M	M	E	18	0	1,692	8,874
BIC Selected	R	—	E, M	M	E	11	1,089	2,123	6,512
Selective Caution Effect	E, R	—	S, M	M	—	12	1,731	2,859	7,647
AIC Selected	E, R	—	S, M	M	—	12	1,731	2,859	7,647
BIC Selected	E	—	S, M	M	—	10	2,212	3,152	7,142

*Note.* LBA = linear ballistic accumulator; *B* = the distance from the upper bound of the start-point distribution (which begins at zero) to the threshold; *A* = the upper bound of the start-point distribution (which begins at zero); *v* = mean drift rate; *sv* = standard deviation of drift rate; *t<sub>0</sub>* = the lower bound of the uniformly distributed non-decision time; *k* = number of model parameters; D = deviance; AIC = Akaike information criterion; BIC = Bayesian information criterion; E = speed versus accuracy emphasis; R = the parameter changes between the dark and light response accumulators; S = mnemonic stimulus manipulation with two levels (test item either previously studied or not); M = the parameter takes on one value for accumulators whose response matches the stimulus and a different value for accumulators whose response fails to match the stimulus. D, AIC, and BIC were calculated by summing deviance and the number of model parameters (*k*) for fits to individual participants and the number of data points per participant over participants. Values for these statistics in the table have the deviance for the least constrained model subtracted, and cannot be compared between Tables 6 and 7 due to differences in estimation procedures. The AIC and BIC selected models have minimum AIC and BIC values within the full set of models (rows 2 and 3) or within the set of model for which caution does not influence drift rate parameters (rows 5 and 6). Table entries of E, S, R, M describe which factors influenced each parameter, and em dashes signify parameters that were constant across all factors.



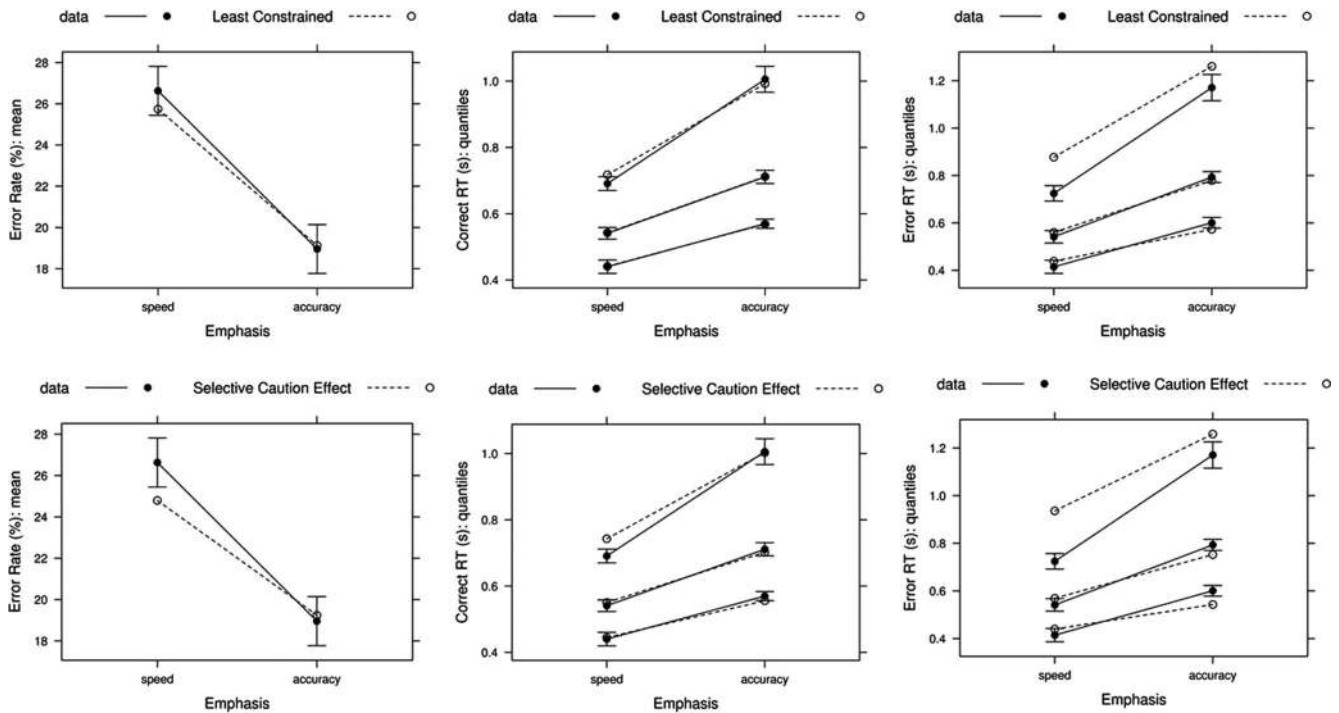


Figure 6. Diffusion model fits to recognition memory data. Response accuracy (left column), and response time (RT) distributions for correct responses (middle column) and error responses (right column). For RT distributions, the lines from bottom to top correspond to 10th, 50th and 90th percentiles. In all panels, the data are shown by solid lines and symbols and diffusion model fits by open symbols and dotted lines. Model fits are averaged over participants and stimulus conditions. Data points are accompanied by 95% with-subject confidence intervals (Morey, 2008). The top row shows fits of the “Least Constrained” model specified in Table 6. The bottom row shows fits of the “Selective Caution Effect” model specified in Table 6.

occurred because the difference between match and mismatch rates (analogous to drift rate in the diffusion model) was smaller under speed (0.85) than accuracy (1.58) emphasis,  $F(1, 46) = 33.4$ ,  $p < .001$ , with this difference being larger for new stimuli (0.82 vs. 2) than old stimuli (0.88 vs. 1.16). Hence, both models supported an effect of emphasis on drift rate that was strongest for new stimuli.

## Discussion

The results of both the diffusion and LBA model analyses indicate a failure of the selective caution effect assumption for the recognition memory data. Once again the failure of selective influence was larger for the LBA model than the diffusion model, but for both models all of our tests—AIC, BIC,  $\chi^2$  and significance tests on the least constrained model parameter estimates—supported a failure of the selective influence assumption. As for the perceptual and lexical paradigms the strongest effect of imposing selective influence was to underestimate the effect of speed versus accuracy emphasis instructions on observed error rates. Further, in the diffusion model fit to the recognition memory data, the selective influence assumption also caused some problems with the fit for the RT data. In agreement with findings for the lexical decision experiment the effect of emphasis on rates interacted with stimulus, being greatest for new stimuli in recognition memory.

Starns et al. (2012) reported evidence based on BIC for a failure of selective influence (slower drift rates in the speed than accuracy emphasis condition) in fits of the diffusion model to their recognition memory data. They noted that the average RT in their speed condition was very fast (526 ms), which they attributed to practice, as their participants performed 20 sessions. Starns et al. suggested that the fast RTs for their speed condition may have weakened mnemonic evidence, and so decreased drift rates, by impairing participants' ability to form effective retrieval cues. They contrasted (p. 14) the considerably faster RTs for their speed condition (526 ms) with the 580 ms RTs in Ratcliff, Thapar, and McKoon's (2004) for their young participants in their speed condition and concluded that Ratcliff et al.'s data supported the selective influence assumption for the diffusion model because of their participant's overall longer RTs.

However, it is possible that neither practice nor extremely fast RTs explain the difference in selective influence, as Ratcliff and Smith (2004) did not report any test of selective influence, and there is evidence of substantial misfit for their model (see their Figure 3). Our recognition memory experiment used only two sessions and mean RT even in our speed-emphasis condition was slower than in Starns et al. (2012, 0.55 s). This suggests that neither extensive practice nor the fast RTs in the speed condition of Starns et al.'s participants may be necessary for a failure of the

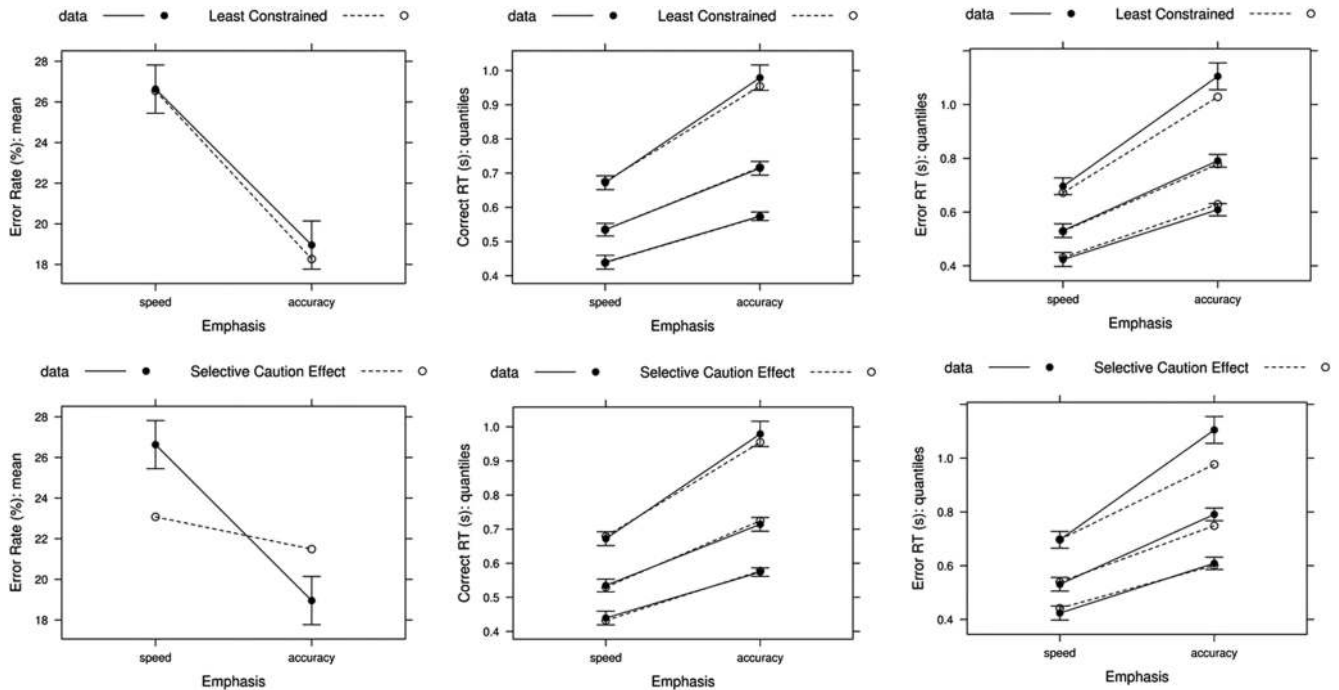


Figure 7. Linear ballistic accumulator (LBA) model fits to recognition memory data. Response accuracy (left column), and response time (RT) distributions for correct responses (middle column) and error responses (right column). For RT distributions, the lines from bottom to top correspond to 10th, 50th and 90th percentiles. In all panels, the data are shown by solid lines and symbols and diffusion model fits by open symbols and dotted lines. Model fits are averaged over participants and stimulus conditions. Data points are accompanied by 95% with-subject confidence intervals (Morey, 2008). The top row shows fits of the “Least Constrained” model specified in Table 7. The bottom row shows fits of the “Selective Caution Effect” model specified in Table 7.

selective caution effect assumption. Regardless, their suggestion that compromised retrieval-cue encoding is the cause remains viable, as discuss further below.

### General Discussion

One of the most useful features of decision-making models is that they tease apart the effects of different cognitive changes that might otherwise be confused. This feature has proven useful in applied studies, for example in understanding the cognitive effects of aging (Forstmann et al., 2011; Ratcliff, Thapar, & McKoon, 2006a, 2006b, 2007, 2011) alcohol use (van Ravenzwaaij et al., 2012), sleep deprivation (Ratcliff & Van Dongen, 2011), and

practice (Heathcote & Hayes, 2012). The ability to attribute different cognitive effects to different model parameters has even been taken as evidence in favor of the models themselves, and subsequently as a benchmark test that new decision-making theories must pass. Data from our three experiments using very different cognitive tasks and converging analytic procedures provide strong evidence against one of the most fundamental assumptions of selective influence: the assumption that changes in decision caution can be explained by changes in the amount of evidence required to trigger a decision, without positing changes in the quality of that evidence.

Using two different decision-making models, diffusion and LBA models, we found that that an emphasis on accurate decision making led to both an increase in the amount of evidence required to trigger a decision and an increase in the quality of evidence extracted from the stimulus. In the parlance of evidence accumulation models, speed–accuracy tradeoffs influenced both the decision threshold (or boundary separation) and the drift rate. Our findings depart from dozens of prior studies, all of which modeled the effects of speed–accuracy manipulations without changes in drift rate parameters, by allowing changes only in the amount of evidence required to trigger a decision, and sometimes in the time taken for nondecision processes such as button pressing. Our results do not provide evidence against the models themselves, but rather against the way the models are linked with data. This changes the approach that ought to be taken in the many applica-

Table 8  
Drift Rate Parameter Estimates From the Least Constrained Diffusion and LBA Models Fit to Our Recognition Data

Model	Parameter	Speed emphasis		Accuracy emphasis	
		New	Old	New	Old
Diffusion	$v$	0.216	0.298	0.245	0.286
LBA	$v(\text{match})$	3.48	3.58	4.03	3.78
LBA	$v(\text{mismatch})$	2.66	2.70	2.03	2.62

Note. LBA = linear ballistic accumulator;  $v$  = mean drift rate.

tions of evidence accumulation models to clinical and cognitive investigations.

It is possible that the difference between our finding and prior work can be explained by the approach taken to model selection. Most previous studies have used a confirmatory approach, where the selective influence of speed–accuracy tradeoffs on threshold parameters is assumed a priori, and good fits to data are taken as support for the assumption. In contrast, we directly compared models that did and did not make the assumption of selective influence, and we found better support for the latter sort. Reassuringly, our findings align with some previous studies that have tested the assumption of selective influence. [Vanderkerckhove et al. \(2008\)](#) and [Starns et al. \(2012\)](#) used Ratcliff's diffusion model and found that speed-emphasis instructions sometimes led to lower drift rate estimates than accuracy-emphasis instructions in a recognition memory task. [Heathcote and Love \(2012\)](#) found the same result in an LBA analysis of [Wagenmakers et al.'s \(2008\)](#) data. However, our results differ from some very new results reported by [Starns and Ratcliff \(in press\)](#). Starns and Ratcliff examined the effects of speed vs. accuracy emphasis on drift rates in a variety of data sets (see their [Table 1](#)) and found no evidence that drift rates varied as a function of emphasis.

All these previous results, combined with our own, rule out several hypotheses about what conditions might cause drift rate differences between speed-emphasis and accuracy-emphasis conditions. Nevertheless, some plausible hypotheses remain consistent with all the results so far. For example, it may be that very fast responses under speed stress are the key element ([Starns & Ratcliff's, in press](#), data sets did not have such responses). Alternatively, it may be that a large difference in the accuracy of responses under speed vs. accuracy emphasis is key. These hypotheses are the subject of ongoing research.

## Theoretical Implications

Our results raise the question of how a decision maker might change the quality of information extracted from the stimulus in response to speed vs. accuracy emphasis instructions. One hypothesis is suggested by prior studies showing that the information extracted from a decision stimulus can change in quality during the course of a single decision. [Ratcliff and McKoon \(1989\)](#), also [Gronlund & Ratcliff, 1989](#)) analyzed data from a recognition memory task in which participants sometimes had to judge whether an item had previously been studied (item recognition) and sometimes had to judge whether a pair of previously studied items had been studied together, or in different pairings. They observed that information about item recognition became available earlier in a decision than information about associative recognition. [Cohen and Nosofsky \(2003\)](#) identified similar effects through experimental manipulation of stimulus structure in a multidimensional categorization task, finding that information from one dimension was usually processed earlier than information from other dimensions. In some cases, this effect could lead to information favoring opposite responses to accumulate early vs. late in the decision process. [Smith and Ratcliff \(2009\)](#) identified related changes in the nature of information extracted from a stimulus during the course of simple perceptual decisions.

These findings bear a suggestive relationship to ours: When decision times are shortened (e.g., by emphasizing response speed

rather than accuracy), the type of information being accumulated could change, because less of the later-arriving information would be available. Because of the unitary nature of our stimuli, it is not obvious what kinds of information might be accumulated in early versus late processing, but many hypotheses are plausible. For example, in our Experiment 1, perhaps small patches of the perceptual stimuli are processed early—leading to greater variability between stimulus samples, and so lower drift rates—and these patches are only later integrated into more informative global precepts. [Starns and Ratcliff \(in press\)](#) suggested a similar explanation for their finding that drift rates were lower under speed emphasis than accuracy emphasis in a recognition memory task. Starns et al. attributed the lower drift rates to compromised retrieval cues in the very fast decisions made under speed-emphasis and noted that this fits with recent memory models, some of which assume that memory probes have few active features early in a test trial, with additional features filling in over time ([Diller, Nobel, & Shiffrin, 2001](#); [Malmberg, 2008](#); see p. 19 of [Starns and Ratcliff, in press](#), for more detail).

These ideas hinge on the assumption that the quality of information extracted from the environment improves systematically during a decision, such that faster decisions will necessarily be based on poorer information than slow decisions. Hence, these ideas are consistent with a broader notion of selective influence in the sense of assuming that the information extracted from the stimulus *at any given time during a decision* is not influenced by speed–accuracy tradeoffs. That is, even though the rate of information extraction might change during a decision, this change is identical in the speed and accuracy emphasis conditions.

A more radical hypothesis allows the information extracted from the stimulus at all moments during decision making to differ between speed-emphasis and accuracy-emphasis conditions. Even this more radical assumption is not without precedent. One possibility is that average information quality is decreased under speed-emphasis purely because some decision-makers, on some trials, resort to uninformed guessing. Although simple, this explanation is hard to reconcile with data from high-accuracy experiments with small differences between speed- and accuracy-emphasis conditions, in which the assumption of selective influence nevertheless fails (e.g., [Vanderkerckhove et al., 2008](#)).

Recent studies of the neurobiology of simple decisions suggest two further possibilities. First, [Ho et al. \(2012\)](#) examined fine perceptual discriminations, similar to the brightness task used here. For such tasks, neurons in lower visual cortex have simple tuning functions: each responds maximally to a preferred stimulus, with outputs that decrease with distance from the preferred stimulus. The particular bell-shape of the tuning curve leads to the curious property that the most active neurons (those tuned to prefer the presented stimulus magnitude, “on-tuned”) are not the most informative neurons on which to base a decision. Instead, the most informative neurons are those tuned slightly away from the presented stimulus (“off-tuned”; [Scolari & Serences, 2009](#)). Ho et al. showed that, when decision accuracy was emphasized, responses were best predicted by activity of the most informative off-tuned neurons, but when decision speed was emphasized, responses were better predicted by the activity of the less informative, but more active, on-tuned neurons. This suggests that decision-makers might base their evidence accumulation on different neural inputs under speed versus accuracy emphasis, with accuracy emphasis

resulting in slower, but more informative information being accrued than speed emphasis. This suggestion which agrees with single-cell recordings from monkeys (Heitz & Schall, 2012) in which neurons in regions implicated in decision making increased their firing rates differently depending on whether speed or accuracy was emphasized.

Second, Ratcliff, Hasegawa, Hasegawa, Smith, and Segraves (2007) recorded firing directly from the cells of monkeys who were performing a simple decision task and identified the firing rate of those cells with the process of evidence accumulation. They noted a brief period when evidence accumulates indiscriminately, in favor of both responses, just after stimulus presentation. This phenomenon could correspond to a period of low-drift rate accumulation early during the decision process, which is consistent with our results, as discussed above.

### Limitations and Further Research

Our model selection methods, although a substantial advance over not testing the assumption of selective influence at all, are still far from optimal. Reassuringly, the model selection methods we employed mostly provided converging evidence, but these methods do not employ state of the art mechanisms for assessing the relative complexity of different theories (e.g., AIC and BIC simply count the number of estimated parameters in a model to measure its complexity). New Bayesian approaches to evidence accumulation models open up the possibility of using much more sophisticated model selection methods. Vanderkerckhove et al. (2008) reanalyzed data reported by Ratcliff and Rouder (1998) using Monte-Carlo methods to sample from posterior distributions for the parameters, and based their model selection on analyses of parameter estimates. With these methods, Vandekerckhove et al. came to a conclusion similar to ours.

A limitation of our analyses, and of evidence accumulation models in general, is that measurements of drift rates confound the effects of *better* information accumulation with the effects of *faster* information accumulation. The improved drift rates observed under accuracy emphasis reflect more diagnostic information being accumulated sooner, but this could equally well occur because all information is being accumulated faster (i.e., faster evidence accumulation overall), or because higher quality information is being accumulated (but without an overall increase in rate).

Evidence accumulation models, and the assumption of selective influence, have been applied to data from dozens of different paradigms. We found evidence against the assumption using data from perceptual decisions, lexical decisions and recognition memory decisions. Further investigation will be required to determine if other paradigms yield similar evidence. Two notable features of the data from our brightness discrimination task were the low overall accuracy rates (around 70%) and the very large differences in accuracy rate between speed-emphasis and accuracy-emphasis conditions (about 17%). It is tempting to speculate that these conditions are prerequisites for a failure of the selective influence of caution. However, our analyses of Wagenmakers et al.'s (2008) lexical decision data speak against this idea. Wagenmakers et al.'s data had high accuracy (around 90%) with a smaller difference between speed and accuracy emphasis (about 10%), but still showed a failure of the selective influence hypothesis. Similarly,

Vanderkerckhove et al.'s (2008) analysis reached similar conclusions to ours but used data from Ratcliff and Rouder (1998) that included many conditions with almost perfect accuracy and very small changes between speed- and accuracy-emphasis conditions (less than 5%). Again, further investigation will be required to determine if there are particular conditions under which caution does not influence the rate at which information is accumulated. However, our results do clearly indicate that there are at least some conditions and paradigms where this assumption cannot be safely made.

### Conclusions

A common assumption in both the development and application of decision-making theories is that changes in decision caution (fast and careless vs. slow and careful) are due to changes in the amount of evidence required to trigger a decision and are not due to changes in the nature of the evidence. Our data challenge this assumption. The most immediate implication is that applications of decision-making models to data should not assume selective influence by fiat but should instead use model selection methods to see if the assumption is warranted in each data set. A more far-reaching conclusion is that theoretical development in simple decision making may have been a little more heavily influenced than needed though the use of the selective influence assumption as a benchmark test. This could warrant the reinvestigation of some earlier theoretical conclusions about competing models.

### References

- Brown, S., & Heathcote, A. (2005). A ballistic model of choice response time. *Psychological Review*, 112, 117–128. doi:10.1037/0033-295X.112.1.117
- Brown, S. D., & Heathcote, A. (2008). The simplest complete model of choice reaction time: Linear ballistic accumulation. *Cognitive Psychology*, 57, 153–178. doi:10.1016/j.cogpsych.2007.12.002
- Burnham, K. P., & Anderson, D. R. (2002). *Model selection and inference: A practical information-theoretic approach*. New York, NY: Springer.
- Busemeyer, J. R., & Wang, Y. I. (2000). Model comparisons and model selections based on generalization criterion methodology. *Journal of Mathematical Psychology*, 44, 171–189. doi:10.1006/jmps.1999.1282
- Churchland, A. K., Kiani, R., & Shadlen, M. N. (2008). Decision-making with multiple alternatives. *Nature Neuroscience*, 11, 693–702. doi:10.1038/nn.2123
- Cohen, A. L., & Nosofsky, R. M. (2003). An extension of the exemplar-based random-walk model to separable-dimension stimuli. *Journal of Mathematical Psychology*, 47, 150–165. doi:10.1016/S0022-2496(02)00031-7
- Coltheart, M. (1981). The MRC psycholinguistic database. *The Quarterly Journal of Experimental Psychology A: Human Experimental Psychology*, 33, 497–505. doi:10.1080/14640748108400805
- Diller, D. E., Nobel, P. A., & Shiffrin, R. M. (2001). An ARC-REM model for accuracy and response time in recognition and recall. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 27, 414–435. doi:10.1037/0278-7393.27.2.414
- Donkin, C., Brown, S. D., & Heathcote, A. (2011). Drawing conclusions from choice response time models: A tutorial. *Journal of Mathematical Psychology*, 55, 140–151. doi:10.1016/j.jmp.2010.10.001
- Donkin, C., Brown, S., Heathcote, A., & Wagenmakers, E.-J. (2011). Diffusion versus linear ballistic accumulation: Different models but the same conclusions about psychological processes? *Psychonomic Bulletin & Review*, 18, 61–69. doi:10.3758/s13423-010-0022-4



- Eidels, A., Donkin, C., Brown, S. D., & Heathcote, A. (2010). Converging measures of workload capacity. *Psychonomic Bulletin & Review*, 17, 763–771. doi:10.3758/PBR.17.6.763
- Forstmann, B. U., Dutilh, G., Brown, S., Neumann, J., von Cramon, D. Y., Ridderinkhof, K. R., & Wagenmakers, E. J. (2008). Striatum and pre-SMA facilitate decision-making under time pressure. *PNAS Proceedings of the National Academy of Sciences of the United States of America*, 105, 17,538–17,542. doi:10.1073/pnas.0805903105
- Forstmann, B. U., Tittgemeyer, M., Wagenmakers, E.-J., Derrfuss, J., Imperati, D., & Brown, S. D. (2011). The speed–accuracy tradeoff in the elderly brain: A structural model-based approach. *The Journal of Neuroscience*, 31, 17242–17249. doi:10.1523/JNEUROSCI.0309-11.2011
- Gold, J. I., & Shadlen, M. N. (2007). The neural basis of decision making. *Annual Review of Neuroscience*, 30, 535–574. doi:10.1146/annurev.neuro.29.051605.113038
- Gronlund, S. D., & Ratcliff, R. (1989). Time course of item and associative information: Implications for global memory models. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 15, 846–858. doi:10.1037/0278-7393.15.5.846
- Hawkins, G., Brown, S. D., Steyvers, M., & Wagenmakers, E.-J. (2012). Context effects in multi-alternative decision making: Empirical data and a Bayesian model. *Cognitive Science*, 36, 498–516. doi:10.1111/j.1551-6709.2011.01221.x
- Hawkins, G. E., Marley, A. A. J., Heathcote, A., Flynn, T. N., Louviere, J. J., & Brown, S. D. (in press). Integrating cognitive process and descriptive models of attitudes and preferences. *Cognitive Science*.
- Heathcote, A., & Brown, S. D. (2004). Reply to Speckman and Rouder: A theoretical basis for QML. *Psychonomic Bulletin & Review*, 11, 577–578. doi:10.3758/BF03196614
- Heathcote, A., Brown, S. D., & Mewhort, D. J. K. (2002). Quantile maximum likelihood estimation of response time distributions. *Psychonomic Bulletin & Review*, 9, 394–401. doi:10.3758/BF03196299
- Heathcote, A., & Hayes, B. (2012). Diffusion versus linear ballistic accumulation: Different models for response time with different conclusions about psychological mechanisms? *Canadian Journal of Experimental Psychology*, 66, 125–136. doi:10.1037/a0028189
- Heathcote, A., & Love, J. (2012). Linear deterministic accumulator models of simple choice. *Frontiers in Psychology*, 3, 292.
- Heitz, R. P., & Schall, J. D. (2012). Neural mechanisms of speed–accuracy tradeoff. *Neuron*, 76, 616–628. doi:10.1016/j.neuron.2012.08.030
- Ho, T. C., Brown, S., & Serences, J. T. (2009). Domain general mechanisms of perceptual decision making in human cortex. *The Journal of Neuroscience*, 29, 8675–8687. doi:10.1523/JNEUROSCI.5984-08.2009
- Ho, T. C., Brown, S. D., van Maanen, L., Forstmann, B. U., Wagenmakers, E.-J., & Serences, J. T. (2012). The optimality of sensory processing during the speed–accuracy tradeoff. *The Journal of Neuroscience*, 32, 7992–8003. doi:10.1523/JNEUROSCI.0340-12.2012
- Kass, R. E., & Raftery, A. E. (1995). Bayes factors. *Journal of the American Statistical Association*, 90, 773–795. doi:10.1080/01621459.1995.10476572
- Malmberg, K. J. (2008). Recognition memory: A review of the critical findings and an integrated theory for relating them. *Cognitive Psychology*, 57, 335–384. doi:10.1016/j.cogpsych.2008.02.004
- McElree, B., & Doshier, B. A. (1989). Serial position and set size in short-term memory: The time course of recognition. *Journal of Experimental Psychology: General*, 118, 346–373. doi:10.1037/0096-3445.118.4.346
- Meyer, D. E., Irwin, D. E., Osman, A. M., & Kounios, J. (1988). The dynamics of cognition and action: Mental processes inferred from speed–accuracy decomposition. *Psychological Review*, 95, 183–237. doi:10.1037/0033-295X.95.2.183
- Morey, R. D. (2008). Confidence intervals from normalized data: A correction to Cousineau (2005). *Tutorials in Quantitative Methods in Psychology*, 4, 61–64.
- Myung, I. J., & Pitt, M. A. (1997). Applying Occam's razor in modeling cognition: A Bayesian approach. *Psychonomic Bulletin & Review*, 4, 79–95. doi:10.3758/BF03210778
- Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, 85, 59–108. doi:10.1037/0033-295X.85.2.59
- Ratcliff, R. (1988). Continuous versus discrete information processing: Modeling the accumulation of partial information. *Psychological Review*, 95, 238–255. doi:10.1037/0033-295X.95.2.238
- Ratcliff, R. (2006). Modeling response signal and response time data. *Cognitive Psychology*, 53, 195–237. doi:10.1016/j.cogpsych.2005.10.002
- Ratcliff, R., Hasegawa, Y. T., Hasegawa, Y. P., Smith, P. L., & Segraves, M. A. (2007). Dual diffusion model for single-cell recording data from the superior colliculus in a brightness-discrimination task. *Journal of Neurophysiology*, 97, 1756–1774. doi:10.1152/jn.00393.2006
- Ratcliff, R., & McKoon, G. (1989). Similarity information versus relational information: Differences in the time course of retrieval. *Cognitive Psychology*, 21, 139–155. doi:10.1016/0010-0285(89)90005-4
- Ratcliff, R., & McKoon, G. (1995). Sequential effects in lexical decision: Tests of compound cue retrieval theory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 21, 1380–1388. doi:10.1037/0278-7393.21.5.1380
- Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological Science*, 9, 347–356. doi:10.1111/1467-9280.00067
- Ratcliff, R., & Smith, P. L. (2004). A comparison of sequential sampling models for two-choice reaction time. *Psychological Review*, 111, 333–367. doi:10.1037/0033-295X.111.2.333
- Ratcliff, R., Thapar, A., & McKoon, G. (2004). A diffusion model analysis of the effects of aging on recognition memory. *Journal of Memory and Language*, 50, 408–424. doi:10.1016/j.jml.2003.11.002
- Ratcliff, R., Thapar, A., & McKoon, G. (2006a). Aging and individual differences in rapid two-choice decisions. *Psychonomic Bulletin & Review*, 13, 626–635. doi:10.3758/BF03193973
- Ratcliff, R., Thapar, A., & McKoon, G. (2006b). Aging, practice, and perceptual tasks: A diffusion model analysis. *Psychology and Aging*, 21, 353–371. doi:10.1037/0882-7974.21.2.353
- Ratcliff, R., Thapar, A., & McKoon, G. (2007). Application of the diffusion model to two-choice tasks for adults 75–90 years old. *Psychology and Aging*, 22, 56–66. doi:10.1037/0882-7974.22.1.56
- Ratcliff, R., Thapar, A., & McKoon, G. (2010). Individual differences, aging, and IQ in two-choice tasks. *Cognitive Psychology*, 60, 127–157. doi:10.1016/j.cogpsych.2009.09.001
- Ratcliff, R., Thapar, A., & McKoon, G. (2011). Effects of aging and IQ on item and associative memory. *Journal of Experimental Psychology: General*, 140, 464–487. doi:10.1037/a0023810
- Ratcliff, R., & Tuerlinckx, F. (2002). Estimating parameters of the diffusion model: Approaches to dealing with contaminant reaction times and parameter variability. *Psychonomic Bulletin & Review*, 9, 438–481. doi:10.3758/BF03196302
- Ratcliff, R., & Van Dongen, H. P. A. (2011). A diffusion model for one-choice reaction time tasks and the cognitive effects of sleep deprivation. *PNAS Proceedings of the National Academy of Sciences of the United States of America*, 108, 11285–11290. doi:10.1073/pnas.1100483108
- Roitman, J. D., & Shadlen, M. N. (2002). Response of neurons in the lateral intraparietal area during a combined visual discrimination reaction time task. *The Journal of Neuroscience*, 22, 9475–9489.
- Rouder, J. N. (2000). Assessing the roles of change discrimination and accumulation: Evidence for a hybrid model of perceptual decision-making in luminance discrimination. *Journal of Experimental Psychology: Human Perception and Performance*, 26, 359–378. doi:10.1037/0096-1523.26.1.359

- Scolari, M., & Serences, J. T. (2009). Adaptive allocation of attentional gain. *The Journal of Neuroscience*, 29, 11933–11942. doi:10.1523/JNEUROSCI.5642-08.2009
- Shurman, B., Horan, W. P., & Neuchterlein, K. H. (2005). Schizophrenia patients demonstrate a distinctive pattern of decision-making impairment on the Iowa Gambling Task. *Schizophrenia Research*, 72, 215–224. doi:10.1016/j.schres.2004.03.020
- Smith, P. L., & Ratcliff, R. (2009). An integrated theory of attention and decision making in visual signal detection. *Psychological Review*, 116, 283–317. doi:10.1037/a0015156
- Speckman, P. L., & Rouder, J. N. (2004). A comment on Heathcote, Brown, and Mewhort's QMLE method for response time distributions. *Psychonomic Bulletin & Review*, 11, 574–576. doi:10.3758/BF03196613
- Starns, J. J., & Ratcliff, R. (2010). The effects of aging on the speed–accuracy compromise: Boundary optimality in the diffusion model. *Psychology and Aging*, 25, 377–390. doi:10.1037/a0018022
- Starns, J. J., Ratcliff, R., & McKoon, G. (2012). Evaluating the unequal-variability and dual-process explanations of zROC slopes with response time data and the diffusion model. *Cognitive Psychology*, 64, 1–34. doi:10.1016/j.cogpsych.2011.10.002
- Starns, J. J., & Ratcliff, R. (in press). Validating the unequal-variance assumption in recognition memory using response time distributions instead of ROC functions: A diffusion model analysis. *Journal of Memory and Language*.
- Usher, M., & McClelland, J. L. (2001). The time course of perceptual choice: The leaky, competing accumulator model. *Psychological Review*, 108, 550–592. doi:10.1037/0033-295X.108.3.550
- Vanderkerckhove, J., Tuerlinckx, F., & Lee, M. D. (2008). A Bayesian approach to diffusion process models of decision-making. In V. Sloutsky, B. Love & K. McRae (Eds.), *Proceedings of the 30th annual conference of the Cognitive Science Society* (pp. 1429–1434). Austin, TX: Cognitive Science Society.
- van Ravenzwaaij, D., Dutilh, G., & Wagenmakers, E.-J. (2012). A diffusion model decomposition of the effects of alcohol on perceptual decision making. *Psychopharmacology*, 219, 1017–1025. doi:10.1007/s00213-011-2435-9
- Voss, A., Rothermund, K., & Voss, J. (2004). Interpreting the parameters of the diffusion model: An empirical validation. *Memory & Cognition*, 32, 1206–1220. doi:10.3758/BF03196893
- Wagenmakers, E.-J., & Farrell, S. (2004). AIC model selection using Akaike weights. *Psychonomic Bulletin & Review*, 11, 192–196. doi:10.3758/BF03206482
- Wagenmakers, E.-J., Ratcliff, R., Gomez, P., & McKoon, G. (2008). A diffusion model account of criterion shifts in the lexical decision task. *Journal of Memory and Language*, 58, 140–159. doi:10.1016/j.jml.2007.04.006
- Wickelgren, W. A. (1977). Speed–accuracy tradeoff and information processing dynamics. *Acta Psychologica*, 41, 67–85. doi:10.1016/0001-6918(77)90012-9

Received October 16, 2012

Revision received December 9, 2013

Accepted December 12, 2013 ■