

Modeling one-choice and two-choice driving tasks

Roger Ratcliff¹

Published online: 6 May 2015
© The Psychonomic Society, Inc. 2015

Abstract An experiment is presented in which subjects were tested on both one-choice and two-choice driving tasks and on non-driving versions of them. Diffusion models for one- and two-choice tasks were successful in extracting model-based measures from the response time and accuracy data. These include measures of the quality of the information from the stimuli that drove the decision process (drift rate in the model), the time taken up by processes outside the decision process and, for the two-choice model, the speed/accuracy decision criteria that subjects set. Drift rates were only marginally different between the driving and non-driving tasks, indicating that nearly the same information was used in the two kinds of tasks. The tasks differed in the time taken up by other processes, reflecting the difference between them in response processing demands. Drift rates were significantly correlated across the two two-choice tasks showing that subjects that performed well on one task also performed well on the other task. Non-decision times were correlated across the two driving tasks, showing common abilities on motor processes across the two tasks. These results show the feasibility of using diffusion modeling to examine decision making in driving and so provide for a theoretical examination of factors that might impair driving, such as extreme aging, distraction, sleep deprivation, and so on.

Keywords Diffusion model · Reaction time · Driving · Decision processes

✉ Roger Ratcliff
ratcliff.22@osu.edu

¹ Department of Psychology, The Ohio State University, Columbus, OH 43210, USA

Introduction

Diffusion decision models have been successful in dealing with simple two-choice decision making tasks (Ratcliff, 1978, Ratcliff & McKoon, 2008, Wagenmakers, 2009). These models have been applied in a variety of domains such as psychology, neuroscience (Gold & Shadlen, 2001, Hanes & Schall, 1996, Philiastides, Ratcliff, & Sajda, 2006, Ratcliff, Cherian, & Segraves, 2003a, Purcell et al., 2010, Smith & Ratcliff, 2004, Wong & Wang, 2006), neuroeconomics and decision making (Roe, Busemeyer, & Townsend, 2001, Krajbich, Armel, & Rangel, 2010), various clinical domains (White, Ratcliff, Vasey, & McKoon, 2010), and with a variety of subject populations such as children (Ratcliff, Love, Thompson, & Opfer, 2012), older adults (Ratcliff, Thapar, & McKoon, 2010), children with ADHD (Mulder et al., 2010), and dyslexia (Zeguers et al., 2011). In these models, evidence towards one or other of the alternatives is assumed to accumulate over time.

A natural extension of these models is to examine simple decision making in driving. The research in this article is designed to apply diffusion models of decision processes to two-choice tasks and compare the results from one-choice models and two-choice models. The experiment reported has four tasks tested on each of 40 subjects. There are two driving tasks and two other tasks that are very similar to the driving tasks but without the driving component. The aim is to see if the diffusion models fit the data, to examine parameter values between tasks, and to examine individual differences across tasks. These results will set the stage for using these models to examine the effects of age, sleep deprivation, alcohol, and other impairments on model components.

Ratcliff and Strayer (2014) examined two driving tasks and the psychomotor vigilance test (PVT)—a task used extensively in sleep deprivation research. All of their tasks required

subjects to respond when a single event was detected, i.e., one-choice tasks. In the PVT, a millisecond timer is displayed on a computer screen and it starts counting up at intervals between 2 and 12 s. after the subject’s last response. The subject’s task is to hit a key as quickly as possible to stop the timer. When the key is pressed, the counter is stopped, and the reaction time (RT) in milliseconds is displayed for 1 s.

The driving tasks used a PC-based driving simulator with a gaming steering wheel and foot pedals. In the one-choice driving task, the subject caught up to a car in front (the lead car). Then, after a delay, the brake lights on the lead car came on, and the subject had to drive around it. Then the subject had to catch up to the lead car in front for the next trial to begin. In the two-choice driving task, the driver caught up to the lead car, then, after a delay, a patch of pixels was presented and the subject had to drive to the right around the lead car if the patch was light, and to the left if the patch was dark. In both tasks, RT was measured from when the steering wheel began to turn.

Ratcliff and Van Dongen (2011) presented a one-boundary diffusion model for performance in one choice tasks and Ratcliff and Strayer (2014) applied the model to driving tasks. In the model, noisy evidence begins accumulating upon presentation of the stimulus until a decision criterion, or boundary, is hit, upon which a response is initiated (Fig. 1, top panel, illustrates the model). In the model, the evidence from the stimulus driving the decision process is termed drift rate. The duration of processes other than the decision process is termed nondecision time and this is another parameter of the model.

Ratcliff and Van Dongen (2011) presented fits of the model to data from the PVT. In one analysis they fit RT distributions (including hazard functions) from experiments with over 2000 observations per RT distribution per subject. They also fit data in which the PVT was tested every 2 h for 36 h of sleep deprivation. They found that drift rate was closely related to an independent measure of alertness and this provided an external validation of the model.

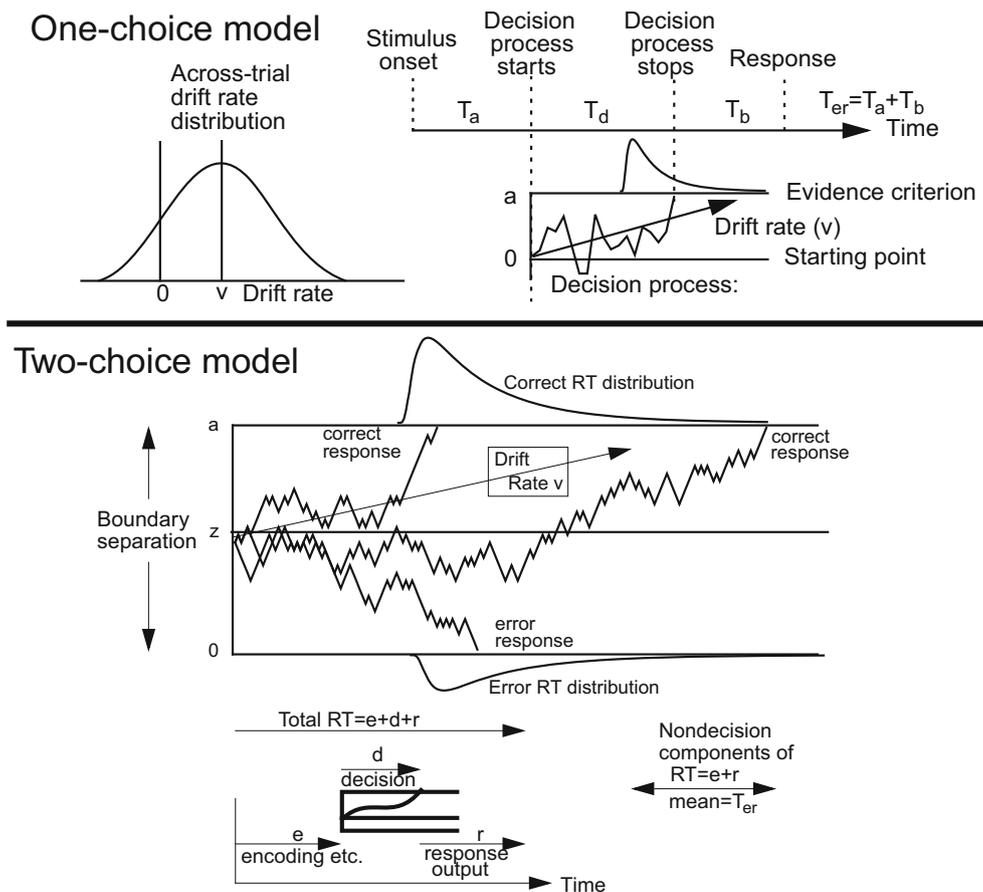


Fig. 1 An illustration of the one-choice and two-choice diffusion models. For the one-choice model, evidence is accumulated at a drift rate v with standard deviation (SD) across trials η , until a decision criterion at a is reached after time T_d . Additional processing times include stimulus encoding time T_a and response output time T_b ; these sum to nondecision time T_{er} , which is assumed to have uniform variability across trials with range s_t . For the two-choice model, three simulated

paths are shown with drift rate v , starting point z , and boundary separation a . Drift rate is distributed normally with SD η and starting point is distributed uniformly with range s_z . Nondecision time is composed of encoding processes, processes that turn the stimulus representation into a decision-related representation, and response output processes. Nondecision time has mean T_{er} and a uniform distribution with range s_t

Ratcliff and Strayer (2014) fit the one-choice model to data from the PVT and two driving tasks and found good fits. They examined individual differences in data and model parameters and found there were correlations in mean RT across the tasks and these were mirrored by correlations in model parameters across tasks. Correlations in drift rate and nondecision time between the two driving tasks were larger than those between the PVT and the driving tasks and this suggests the processing was more similar between the two driving tasks than between either of these and the PVT. They also fit the one-choice diffusion model to data from an experiment by Cooper and Strayer (2008) that examined distracted driving and found that either drift rate was reduced or boundary settings were increased resulting in longer decision times.

Driving, however, is more complicated than just making a series of the same response to the same stimuli in one kind of task. To take the next step, in this article I present data from a driving version of a standard two-choice perceptual brightness discrimination task using stimuli that are arrays of black and white pixels. This task requires one of two responses to one of four different stimuli (with variability in the stimuli so that no two are identical even if they are from the same condition). Along with this I tested subjects on three other tasks: the standard non-driving version of this task, brightness discrimination with button presses (e.g., Ratcliff, 2002, 2014, Ratcliff, Thapar, & McKoon, 2003b), the PVT, and the single-choice driving task described above. The aim was to see whether the models could fit the data from each task, and if they did, how the model parameters differed across tasks, and whether there were consistent individual differences in data and model parameters across tasks. The experiment and modeling allowed us to examine relationships between one-choice and two-choice driving tasks to see if model components were consistent across tasks.

One-choice diffusion model

The one-choice diffusion model (Ratcliff & Van Dongen, 2011) assumes that noisy evidence begins accumulating on presentation of a stimulus until a decision criterion is hit, upon which a response is initiated (Fig. 1 illustrates the model). Within trial variability is set to $s = 0.1$ as in the two-choice model. In the one-choice diffusion model (Ratcliff & Van Dongen, 2011), evidence from the stimulus is not assumed to be identical on each trial. To represent this, drift rate is assumed to vary from trial to trial and it is assumed to be distributed normally with mean ν and SD η . This relates it to the standard two-choice model, which makes this assumption to fit the relative speeds of correct and error responses. In application of the one-choice model to sleep deprivation data, across-trial variability in drift rate was needed to produce the long tails observed in the RT distributions. Also, nondecision

time is assumed to vary from trial to trial, and is assumed to have a uniform distribution with range s_r .

There are five parameters of the decision process that are estimated in fitting the model to data: drift rate, SD in drift rate across trials, mean nondecision time, range of distribution of nondecision time, and distance to the decision boundary. However, there is an issue of identifiability in model parameters in this one-choice model (Ratcliff & Van Dongen, 2011). Only two parameters out of drift rate, across-trial SD in drift rate, or boundary setting can be uniquely determined; two ratios of these can be identified. So absolute sizes of some of the parameters are not unique, but the ratios are. Compounding this issue is that, in the experiments presented in this article, I have relatively low numbers of observations per experiment. This is because the subject is performing a simulated driving task with delays of seconds before decisions are required, unlike standard button-press tasks in which the next stimulus appears shortly after a response. This means that the model parameters are not estimated particularly accurately (across-trial variability in drift rate is estimated less accurately than the other model parameters). This issue was discussed in Ratcliff and Strayer (2014).

Fitting the model

In single-choice decision making tasks, the data to be fit are a distribution of RTs for hitting the response key. For the one-choice diffusion model, there is an explicit solution for the distribution of RTs for a single positive drift rate (the Wald or inverse Gaussian distribution). However, there is no explicit mathematical solution for a RT distribution with negative drift rate. Negative drift rates are produced from the left tail of the across-trial distribution of drift rates (e.g., the area below zero in the distribution of drift rates in Fig. 1). The model was therefore implemented as a simulation using a random walk approximation to the diffusion process with 20,000 iterations with a 0.5-ms step size (Tuerlinckx et al., 2001).

To fit the model to data, the 0.05, 0.10, ..., 0.95 quantiles of the RT distribution were calculated from the data. Because there is only one RT distribution, in earlier work we decided to use as much distributional information as possible, i.e., 19 quantiles instead of 5. With the two-choice model, accuracy and error RT distributions help constrain the model and there is not much difference between 5 and 9 quantiles (Ratcliff & Childers, 2015). The quantile RTs were used to find the proportion of responses in the RT distribution laying between the data quantiles, and these were multiplied by the number of observations to give the expected values (E). The proportions of responses between the data quantiles were 0.05 and these were multiplied by the number of observations to give the observed values (O). In the simulations, a maximum response time was set at 3000 ms and any RT greater than this was set to

this maximum (this occurred on 0.9 % of the time for the PVT and 1.2 % of the time for the driving task). A chi-square statistic $\Sigma(O-E)^2/E$ was computed, and the parameters of the model were adjusted by a simplex minimization routine to minimize the chi-square value. The simplex minimization routine was restarted 18 times with a wide simplex round the parameters estimated from the prior fit (though usually only 4 or 5 were needed). Because of the issue of parameter identifiability, on each run of the fitting routine, boundary separation was fixed at a value I felt appropriate for the data set, in these two experiments, $a = 0.1$ (this value is similar to boundary separation in the two-choice case—results were similar setting $a = 0.15$). In fitting the model, 2000 simulated RTs were generated for each evaluation of the model as in Ratcliff and Van Dongen (2011). The model was fit to the data for each individual subject, which allowed individual difference analyses.

Ratcliff and Strayer (2014) found that more stable estimates of model parameters were obtained when the first and second quantiles were grouped. The problem was that the model parameters were being determined by the behavior of the .05 quantile RT, which can possibly be partly determined by fast outliers. In the modeling presented here, the .1 quantile was the first quantile and so the proportion of responses between 0 and the .05 and between the .05 and .1 quantiles were grouped so no data were ignored.

Two-choice diffusion model

The two-choice diffusion model (Ratcliff, 1978, Ratcliff et al., 1999, Ratcliff & McKoon, 2008, Ratcliff & Smith, 2004) has been applied in a number of domains such as aging, sleep deprivation, depression, and hypoglycemia (Ratcliff, Perea, Colangelo, & Buchanan, 2004a, Ratcliff, Thapar, & McKoon, 2001, 2003, 2004, Ratcliff & Van Dongen, 2009, Spaniol, Madden, & Voss, 2006, White, Ratcliff, Vasey, & McKoon, 2010). These applications introduced new and different interpretations of performance, in particular by taking into account differences in speed–accuracy trade-off settings between individuals. Furthermore, the model has been applied to individual differences in processing (Ratcliff et al., 2010, 2011, Schmiedek et al., 2007).

In the model, noisy evidence is encoded from a stimulus and accumulates from a starting point, “z” in Fig. 1, toward one of two decision criteria. When the amount of accumulated evidence reaches one of the two criteria, a response is executed. In Fig. 1, the arrow illustrates the drift rate. Because of the noise in the accumulation process, the paths from starting point to criterion for an individual word will vary around its drift rate. For the three paths in Fig. 1, one leads to a fast correct decision, one to a slow correct decision, and one to an error. It is the noise that makes the model’s predictions

match the shapes of RT distributions, as shown in the figure. Most responses are reasonably fast, but there are slower ones that spread out the right-hand tails of the distributions. It is also this noise that produces error responses. As the bottom path in the figure illustrates, even when drift rate is positive, the accumulation of evidence can reach the negative criterion by mistake.

As for the one-choice model, outside of the decision process, there are nondecision processes such as stimulus encoding, building a stimulus representation and extracting decision-relevant information from it, and response execution. The total processing time for a decision is the sum of the time taken by the decision process to reach a criterion and the time taken by the nondecision component. Also, drift rate, the settings of the decision criteria, and the nondecision component are assumed to vary across the trials of an experiment. The idea is that participants cannot hold the values exactly constant from one trial to the next. This assumption is essential for the model to account for the relative speeds of correct and error responses (see Ratcliff & McKoon, 2008).

Fitting the model to the data is accomplished by a minimizing routine that adjusts parameter values (drift rate, criteria, the nondecision component, and the variability across trials in each of them) iteratively until the values that best predict the data are obtained (Ratcliff & Tuerlinckx, 2002). Specifically, for each condition in an experiment, quantile RTs are generated and these, along with the model, generate the proportions of predicted responses between the quantiles. These proportions multiplied by the number of observations are used to produce a chi-square value and the model parameters are adjusted to make the chi-square value (summed over conditions and correct and error responses) a minimum. Recently, three software packages have been developed that are in quite wide use (Vandekerckhove & Tuerlinckx, 2008, Voss & Voss, 2007, Wiecki, Sofer, & Frank, 2013, see also Wagenmakers, Van Der Maas, & Grasman, 2007). However, I used my routines because they perform as well as the others (cf., Ratcliff & Childers, 2015).

Experiment

The experiment tested subjects on four tasks. There were one-choice and two-choice driving tasks (drive round the car ahead when the brake light comes on and drive left or right around the car ahead if the stimulus is dark or light, respectively). There was also a brightness discrimination task like the two-choice driving task and the PVT.

Apparatus

The PVT and brightness discrimination task were administered on Thinkpad laptop computers with a 14-inch display;

responses were collected by subjects pressing keys on the attached laptop keyboard. For the two driving tasks, a standard driving game steering wheel and pedal set (Logitech Driving Force GT Wheel with Force Feedback; <http://www.logitech.com>) were used as controls. The driving simulations were run with STISIM Drive version 2 software on a 15.6-inch Dell XPS L502X laptop and events were sampled at a 16.67 ms sampling rate.

Psychomotor vigilance test

The stimulus numbers were displayed in a rectangle on the screen of the laptop at standard viewing distance of 57 cm. The rectangle was 3.5 degrees wide by 1.5 degrees high and was displayed in the middle of the screen, remaining on the screen for the entire experiment. After a delay, a counter appeared inside the rectangle and began counting up from zero in milliseconds. The subject was instructed to press a response key as quickly as possible after the digits appeared. When the key was pressed, the counter stopped, and the RT in milliseconds was displayed on the screen for 1 s. After a 2–12 s delay (uniformly distributed in steps of 1 s), a new counter then appeared for the next trial. If a subject hit the key before the counter began counting, the message “FS” for false start was displayed on the screen. The counter counted up with digits changing every 47 ms but the final number displayed was the best estimate of the actual RT.

Driving-around task

In the simulated driving environment, on each trial, the driver approached a “lead” car driving in the right-hand lane of the 2-lane highway. When the driver was close enough, about 95 feet in the simulation, the lead car wobbled left and right to signal the start of the trial. The driver was instructed to stay about that distance behind the lead car at the speed of the lead car (about 65 mph). After a variable time (between 2 and 10 s in 2-s steps), the brake light of the lead car turned on (see Fig. 2), and the driver had to steer into the left-hand lane as quickly as possible and then allow the lead car to slow down and fall behind. Once that car had receded to the rear, the driver steered back into the right-hand lane, and approached the next lead car.

To measure the time at which the driver started to drive around the lead car, the sideways velocity was recorded and linear interpolation was used to estimate the time at which the car started to move sideways. The sideways velocity starts to increase and then becomes approximately constant for a short while as the car drives to the left around the lead car. Linear interpolation from this relatively constant velocity provides an estimator of when the car begins to turn that is consistent across responses by the subject.

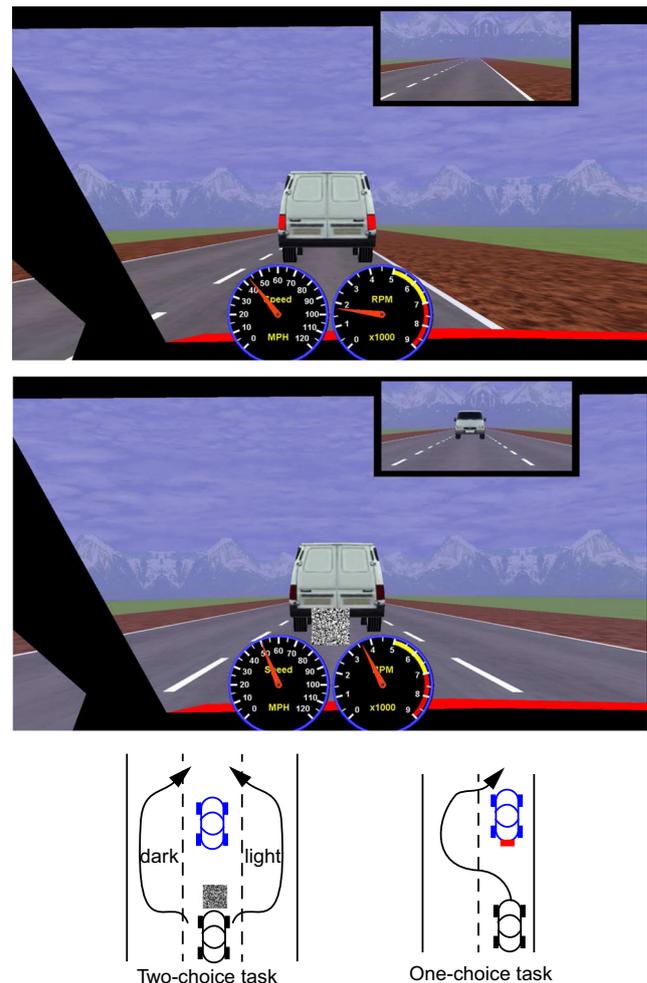


Fig. 2 Screen shots of driving views from the two driving tasks. The top panel shows the lead car with the brake lights on and the middle panel shows the lead car with the brightness stimulus patch. The bottom panel illustrates the two tasks

Brightness discrimination

The stimuli were 64×64 squares of black and white pixels on a grey background (the whole display was 320×200 pixels). The “brightness” of a square was manipulated by varying the probability that a pixel was white. There were four levels of brightness produced with four values for the probability of a pixel being white: 0.43, 0.47, 0.53, and 0.57. Each trial began with a + sign fixation point for 250 ms and then the stimulus was displayed until response. Subjects were instructed to hit the “/” key for bright responses and the “z” key for dark responses quickly and accurately.

Driving-around task with brightness discrimination

The subject was driving in the middle lane on a 3-lane highway. The subject approached the lead car directly ahead in the

middle lane and, as in the single-choice task, when the driver was close enough, about 95 feet in the simulation, the lead car wobbled left and right to signal the start of the trial. The subject was instructed to maintain that distance (at about 65 mph in the simulation). Between 0 and 8 s later (mean 4 s), a 64 × 64 pixel patch appeared in the front of the windshield (see Fig. 2). The proportion of dark and light pixels was the same as for the brightness discrimination task above. For dark patches, the subject was instructed to move into the left lane to pass the lead car and, for bright patches, the subject was instructed to move into the right lane to pass the lead car. After passing the lead car, the subject accelerated, moved back to the middle lane, and approached the next lead car.

Subjects

Forty young adults were recruited through fliers posted in Ohio State University campus buildings. They were asked if they had driving experience and all said they had driven for at least a year several times a week. Subjects participated in five 1-hour sessions. The PVT was administered for the first 10 min during sessions 1–4. The subject spent the remaining time on the driving tasks. In sessions 1 and 3, the subject participated in the driving-around task. In sessions 2 and 4, the subject participated in the two-choice driving-around task. During the last session, the subject was tested on the brightness discrimination task. The subjects were paid US \$12 per session.

Results

For the PVT, one-choice driving task, two-choice driving task, and brightness discrimination task, RTs less than 100, 150, 500, and 350 ms, respectively, and RTs greater than 1200, 1500, 2000, and 2500 ms, respectively were eliminated from the analysis. This eliminated 0.5 %, 2.2 %, 3.0 %, and 4.8 % of the responses for the four tasks, respectively. For the two-choice driving task, and brightness discrimination task, 1.1 % and 3.4 % of the responses (respectively) had RTs below the lower cutoff (and had accuracy at chance). The mean RTs for the one-choice tasks were for the PVT, 329 ms and for the

driving task, 602 ms (see Table 1). For the two-choice tasks, mean correct and error RTs (averaging over conditions) were 1025 ms and 1093 ms, respectively, for the driving task, and 604 ms and 679 ms, respectively, for the brightness discrimination task. One obvious reason that the one-choice and two-choice driving tasks were slower was that they required the steering wheel to be turned, whereas the PVT and brightness discrimination tasks required only button presses. Gomez, Ratcliff, and Childers (manuscript submitted) used a diffusion model to examine performance on a brightness discrimination task with three different response modes: pressing buttons, using a touch screen, and eye movements. They found that the only model parameter that differed among the response modes was nondecision time.

The one-choice diffusion model was fit to the RT distributions for the two one-choice tasks. Because of trade-offs in model parameters (Ratcliff & Van Dongen, 2011), only two ratios of the three model parameters, boundary setting, drift rate, and across-trial variability in drift rate are identifiable. For this reason, I set boundary setting (*a*) to be 0.1 for fits to all the subjects. Model parameters averaged over subjects are shown in Table 1. In general, the model produced fits that closely matched the data. The mean chi-square values averaged over subjects shown in Table 1 are a little higher than the critical values of chi-square with 14 degrees of freedom. The number of observations for the PVT was about 400 and for the driving one-choice task was about 300. Cumulative distributions averaged over subjects are shown in Fig. 3. These show good correspondence between theory and data with one exception: the 0.95 quantile RT (in the extreme tail of the distribution) for the driving around task was shorter than the value that was predicted by the model.

All of the following statistical tests were paired *t*-tests with 39 degrees of freedom and a critical value of 2.02. Drift rate did not differ between the two tasks (*t* = 0.22) but across-trial variability in drift was larger for the driving task than the PVT (*t* = 2.69), which means that the signal-to-noise ratio (discriminability) was a little lower for the driving task.

Nondecision time and across-trial variability in nondecision time are both larger for the driving task than the PVT (*t* = 19.18 and 11.41, respectively). The results show large differences in nondecision time as a function of the response

Table 1 Mean reaction time (RT) and model parameters for one-choice tasks. The RT standard deviations (SDs) are the mean of the SDs for each subject. Parameters: *a* boundary separation, *T_{er}* mean nondecision

component of response time, *η* SD in drift across trials, *s_t* range of the distribution of nondecision times, *v* drift rate. Critical values of chi-squares are 23.7 for 14 degrees of freedom

Parameter	Task	RT (s)	<i>T_{er}</i> (s)	<i>s_t</i> (s)	<i>a</i>	<i>v</i>	<i>η</i>	<i>v/η</i>	<i>χ²</i>
Mean	PVT	0.329	0.224	0.088	0.1	1.152	0.419	2.98	15.0
	Driving	0.603	0.472	0.219	0.1	1.172	0.577	2.18	17.3
SD	PVT	0.059	0.028	0.024		0.430	0.214	0.61	11.3
	Driving	0.151	0.085	0.065		0.481	0.293	0.45	8.9

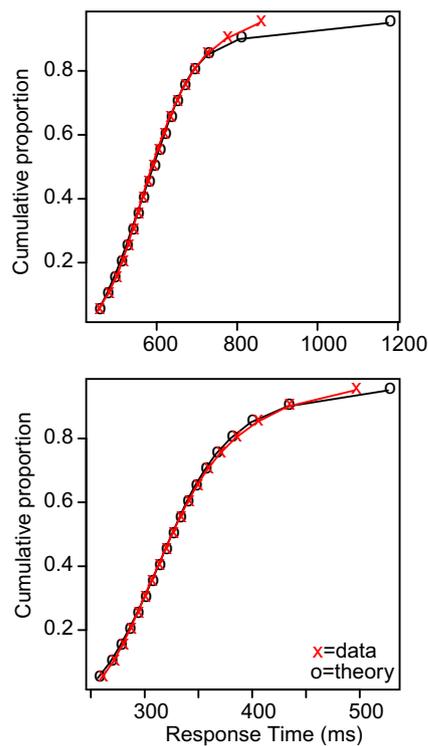


Fig. 3 Cumulative RT distributions averaged over subjects for the psychomotor vigilance test (PVT) task and the one-choice driving task. X Data points, O model predictions

requirement (hitting a button versus moving the steering wheel), but smaller differences in the duration of the decision process. The difference in mean RT between the one-choice driving task and the PVT was 274 ms. In the diffusion model, 248 ms of this difference was accounted for by the difference in nondecision time (Table 1). The decision process accounted for the remaining 26 ms of the difference (i.e., the duration of the decision process was similar for the two tasks).

The two-choice model was fit to the accuracy values and correct and error RT distributions for the four conditions (proportions of white pixels) for the driving task and the brightness discrimination task. The quality of the fits was about the same as other applications of the diffusion model. The mean chi-square value was less than the critical value (47.4 with 33 degrees of freedom) for the driving task, and a little larger for the brightness discrimination task. The quantile RTs averaged over subjects and the predictions averaged over subjects are shown in Fig. 4. Quantile RTs for the most accurate conditions are not shown because there are less than five observations for some of the subjects and so quantiles cannot be computed. Instead, the median RT is presented as an “M” and the figures show they are close to the predicted median RTs.

It may seem counterintuitive that the two-choice driving task has a lower chi-square value than the brightness discrimination task given that the fit is slightly worse by visual inspection (Fig. 4). This is due to the difference in the number of observations per subject which is much higher for the

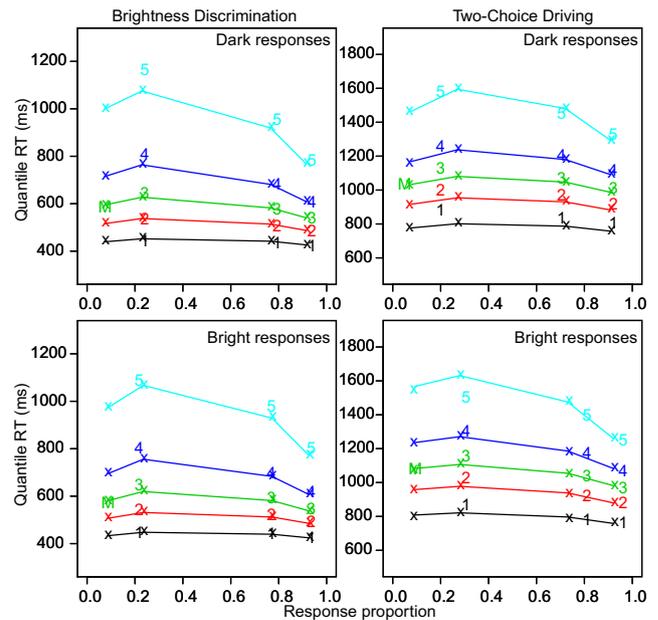


Fig. 4 Quantile-probability functions averaged over subjects for the two-choice tasks. The values on the x-axis represent the proportion of responses for that condition (in the top plots, the conditions from right to left are .43, .47, .53, .57 white pixels, and for the bottom plots the order is reversed). The quantile response times in order from the bottom to the top are the .1, .3, .5, .7, and .9 quantiles. X Data, lines and numbers theoretical fits of the diffusion model

brightness discrimination task (about 1280) than the driving two-choice task (about 300). If there was systematic miss, then because chi-square is based on frequencies, chi-square would increase as the number of observations increases for the same systematic miss.

The model parameters are shown in Table 2. An overall value of drift rate was computed: namely $v_1 + v_2 - v_3 - v_4$, and this represents how well the subjects can discriminate the stimuli averaged over conditions. The drift rates are combined this way so that comparisons can be made with the single drift rate from the one-choice task. The difference in these drift rates between the two-choice tasks was significant ($t = 3.77$). The difference in boundary separation was significant ($t = 2.49$), the difference in nondecision time was significant ($t = 20.98$), the difference in across-trial variability in drift was not significant ($t = 1.99$), the difference in across-trial variability in starting point was significant ($t = 2.42$), and the difference in across-trial variability in nondecision time was significant ($t = 11.99$). The differences between the two tasks in across-trial variability in both drift and starting point are small and not theoretically important. The difference in drift rates between the two tasks suggests that the demands of driving reduced the ability of subjects to discriminate between bright and dark stimuli. But this is qualified by the fact that the displays are somewhat different. As is obvious from Table 2, nondecision time is longer and across-trial variability in nondecision time is larger in the driving task than for the one-choice

Table 2 Diffusion model parameters for two-choice tasks. *a* Boundary separation; *z* starting point; *T_{er}* non-decision component of response time; *η* standard deviation in drift across trials; *s_z* range of the distribution of

starting point (*z*); *s_t* range of the distribution of non-decision times; *p_o* proportion of contaminants; *v* drift rates; χ^2 chi-square; *v₁*, *v₂* dark responses to dark stimuli; *v₃*, *v₄* bright responses to bright stimuli

Statistic	Task	a	T _{er} (s)	η	s _z	p _o	s _t (s)	z	v ₁	v ₂	v ₃	v ₄	χ ²
Mean	Driving	0.136	0.792	0.144	0.038	0.002	0.436	0.065	0.300	0.118	-0.151	-0.371	38.5
	Brightness	0.124	0.397	0.172	0.055	0.006	0.154	0.063	0.389	0.190	-0.182	-0.374	53.9
SD	Driving	0.028	0.117	0.048	0.033	0.005	0.137	0.019	0.108	0.079	0.087	0.121	13.8
	Brightness	0.029	0.033	0.053	0.025	0.010	0.045	0.016	0.120	0.077	0.061	0.089	17.3

experiments. As for the one-choice tasks, this is partly because of the different response requirements in the two tasks.

I examined individual differences in data and model parameters both within and between tasks. Correlations are shown in Table 3 and scatter plots for those of most theoretical interest are shown in Fig. 5. There are a large number of possible correlations that could be examined, but here I focus on the ones that were significant and/or of theoretical interest. With only 40 subjects, correlations above 0.31 are significant and unless the correlation is large, I view the results as suggestive rather than definitive.

For the one-choice tasks, the correlation of mean RT was significant, but the correlations of drift rates and of nondecision time were not significant. This conflicts with the results from Ratcliff and Strayer (2014), who found a significant correlation in drift rates. A key reason for this is the low correlation between mean RTs relative to that in Ratcliff and Strayer (a correlation of 0.57). Inspection of the individual subjects showed some who were very fast at the PVT but quite slow at the driving task. We asked subjects how much driving they did and only used subjects with experience, but they may have been overestimating their experience. Also, they may not have been familiar with using the gaming driving apparatus and this may have produced long RTs in the driving task. Because RT is broken into two components, the correlations of the two components were smaller and not significant.

For the two-choice tasks, there was a significant correlation in accuracy (.40) but a nonsignificant correlation in mean RT (.24). Both boundary separation (.35) and drift rate (.32) correlated between the two tasks (these correlations are just significant so we should not bet the farm on them). Nondecision time did not correlate between the two tasks which suggests

that the different response requirements are important in understanding the speed of decision making in driving tasks.

For the one- and two-choice driving tasks, there were correlations in mean RT, and in nondecision time and drift rate. The .39 correlation between drift rates suggests that cognitive aspects of decision making during driving are important in understanding performance. The high .58 correlation in nondecision time suggests that response requirements play a large role in individual differences in response times in these tasks. This means that in a theoretical examination of driving, the ability of individuals to perform the motor and cognitive aspects of motor control are an important factor that should be taken into account even when examining perceptual or cognitive aspects of performance.

There were also significant correlations in drift rate and nondecision time for the brightness discrimination two-choice task and the PVT one-choice task. These suggest similar processing in the non-driving tasks.

General discussion

The experiment described in this article was made up of four tasks, one- and two-choice driving tasks and one- and two-choice non-driving tasks. The driving and non-driving one-choice tasks were similar in that a response was required at the onset of a stimulus and the driving and non-driving two-choice tasks were both brightness discrimination tasks.

The first main result was that diffusion models fit the data well for all four tasks. The second main result was that mechanisms of performance having to do with perceptual processing and decision making were consistent across the driving

Table 3 Correlations in data and model parameters across tasks

Task pairs	Data or model parameter				
	mean RT	T _{er}	v	Accuracy	a
Driving and PVT one-choice tasks	0.37	0.28	0.14		
Driving two-choice and one-choice tasks	0.58	0.60	0.39		
Driving and brightness two-choice tasks	0.24	0.07	0.32	0.40	0.35
Brightness two-choice and PVT one-choice tasks	-0.12	0.36	0.34		

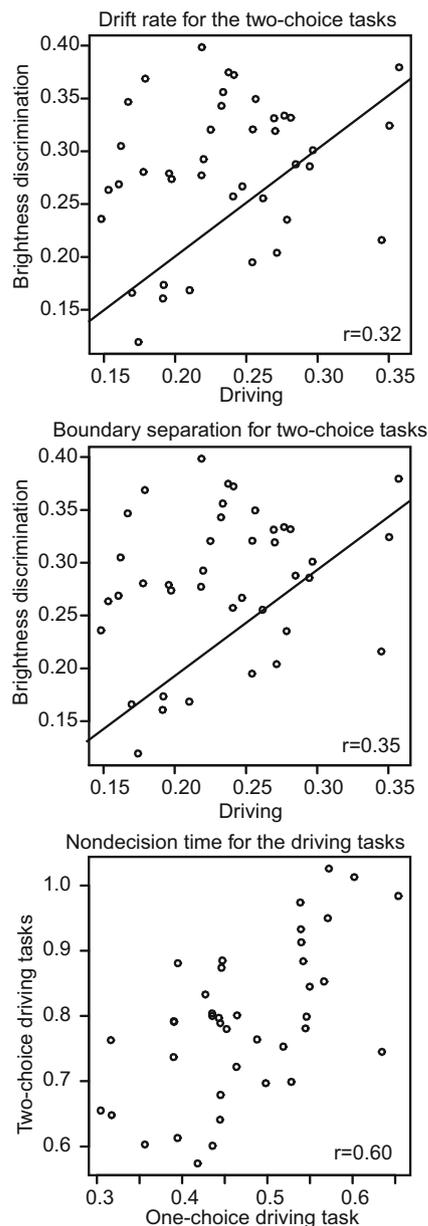


Fig. 5 Three scatter plots. *Top* Drift rates for the two-choice tasks, *middle* boundary separation for the two-choice tasks, *bottom* nondecision time for the two driving tasks

and non-driving tasks. For the two-choice tasks, decision boundaries were similar suggesting settings that are independent of the task (e.g., Ratcliff et al., 2010). Drift rates for the two-choice tasks were a little lower in the driving task (about 15 %), suggesting that the driving requirements (or the difference in the stimulus displays) produced only a modest decrement in perception and decision making. Drift rates were also similar in the one-choice tasks, but across-trial variability in drift rate was larger in the driving task, which made the ratio of drift to variability (signal to noise ratio) lower in the driving task (by about 25 %). These results suggest that in these simple driving tasks with easy driving conditions (without

distractions such as pedestrians, turning, other cars, rain, etc.), there is only a small decrease in evidence used in the decision for performing the task in the driving environment relative to the standard button-pressing environment in typical cognitive experiments.

The third main result was that response processes in the driving environment contributed more to response times than cognitive factors. The difference in nondecision time between the one-choice driving and non-driving tasks was 270 ms (603 vs 329 ms) and the difference was 420 ms between the two-choice driving and non-driving tasks (1025 vs 604 ms). The estimates of decision times in the two one-choice tasks were 100 ms for the non-driving task and 130 ms for driving task. The estimates of decision times in the two two-choice tasks were 207 ms for the non-driving task and 233 ms for the driving task. These results show that response processes in the driving environment contribute more to decision time than cognitive factors. This conclusion is a little more complicated because there are distributions of responses times, nondecision times, and decision times. For example, the .9 quantile RT for correct responses for the two-choice non-driving task is 930 ms and 325 ms to 470 ms is the range of nondecision time. So for the slowest responses, about 450–600 ms is the decision time. Thus, although the above discussion is in terms of the mean time, the discussion has to be understood in terms of the distributions.

The fourth main result was that individual differences in drift rates and in nondecision times provided interpretable patterns across tasks. This provides additional support for the hypothesis that similar decision processes were involved in the one- and two-choice tasks. The most important results were: first, nondecision time correlated significantly across the two driving tasks, and this supports the view that similar motor preparation and execution processes are involved in the one-choice and two-choice driving tasks. Second, drift rates correlated across the two driving tasks and also across the two two-choice tasks. Third, boundary separation correlated across the two two-choice tasks.

Ratcliff and Strayer (2014) compared two one-choice driving tasks and the PVT. The values of the model parameters were similar to the ones from this study (Table 1). Their individual difference analyses showed correlations among mean RTs, nondecision time, and drift rate, but only for drift rate and mean RT for their PVT and driving-around tasks. As noted in the results section, there were some subjects who were fast on the PVT and relatively slow on the driving task. This is shown by the lower correlation between mean RT on the two tasks (.37) in this study compared with the correlation (.57) in the Ratcliff and Strayer study. In Ratcliff and Strayer, nondecision times were not correlated significantly between the PVT and driving task, but drift rates were. Other than this, the two one-choice tasks used here produced similar results to those in the Ratcliff and Strayer study.

In one sense our driving tasks are dual-choice tasks that are similar to standard cognitive psychology ones, but with a different response requirement, but there are additional requirements in the driving task; the driver must attempt to maintain speed, stay in the appropriate lane, and so on. These additional requirements take up processing capacity, but in the easy driving situations of our experiment, the effect is to reduce cognitive performance by only a small amount.

Our main conclusions are that diffusion modeling can be applied fruitfully to driving tasks and that analyses from it can provide important insights into performance. Probably the main reason that this has not been done before is the lack of cheap tools with which to perform these studies. Low-end PC based driving simulators do not have tools to measure RTs without some programming and high quality driving simulators that provide these tools are expensive and are available to very few researchers that might be interested in cognitive modeling. In our study, it was noteworthy that the information from stimuli that drives decision processes was only slightly reduced between the driving and non-driving tasks. The results from this study show that the diffusion modeling approach can be applied to simple driving tasks. This will allow us to determine what components of processing in decision making in driving are affected difficulty of the driving environment and by impairments caused by factors such as alcohol, sleep deprivation, and distracted driving (cf. Ratcliff & Strayer, 2014).

Acknowledgments This article was supported by grant NIA R01-AG041176 and AFOSR grant FA9550-11-1-0130.

References

- Cooper, J. M., & Strayer, D. L. (2008). Effects of simulator practiced and real-world experience on cell-phone related driver distraction. *Human Factors, 50*, 893–902.
- Gold, J. I., & Shadlen, M. N. (2001). Neural computations that underlie decisions about sensory stimuli. *Trends in Cognitive Science, 5*, 10–16.
- Hanes, D. P., & Schall, J. D. (1996). Neural control of voluntary movement initiation. *Science, 274*, 427–430.
- Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience, 13*, 1292–1298.
- Mulder, M.J., Bos, D., Weusten, J.M.H., van Belle, J., van Dijk, S.C., Simen, P., . . . , Durson, S. (2010). Basic impairments in regulating the speed-accuracy tradeoff predict symptoms of attention-deficit/hyperactivity disorder. *Biological Psychiatry, 68*, 1114–1119.
- Philastides, M. G., Ratcliff, R., & Sajda, P. (2006). Neural representation of task difficulty and decision making during perceptual categorization: A timing diagram. *Journal of Neuroscience, 26*, 8965–8975.
- Purcell, B. A., Heitz, R. P., Cohen, J. Y., Logan, G. D., Schall, J. D., & Palmeri, T. J. (2010). Neurally constrained modeling of perceptual decision making. *Psychological Review, 117*, 1113–1143.
- Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review, 85*, 59–108.
- Ratcliff, R. (2002). A diffusion model account of reaction time and accuracy in a two choice brightness discrimination task: Fitting real data and failing to fit fake but plausible data. *Psychonomic Bulletin and Review, 9*, 278–291.
- Ratcliff, R. (2014). Measuring psychometric functions with the diffusion model. *Journal of Experimental Psychology: Human Perception and Performance, 40*, 870–888.
- Ratcliff, R., & Childers, R. (2015). Individual differences and fitting methods for the two-choice diffusion model. *Decision*. (in press).
- Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Computation, 20*, 873–922.
- Ratcliff, R., & Smith, P. L. (2004). A comparison of sequential sampling models for two-choice reaction time. *Psychological Review, 111*, 333–367.
- Ratcliff, R., & Strayer, D. (2014). Modeling simple driving tasks with a one-boundary diffusion model. *Psychonomic Bulletin and Review, 21*, 577–589.
- Ratcliff, R., & Tuerlinckx, F. (2002). Estimating the parameters of the diffusion model: Approaches to dealing with contaminant reaction times and parameter variability. *Psychonomic Bulletin and Review, 9*, 438–481.
- Ratcliff, R., & Van Dongen, H. P. A. (2009). Sleep deprivation affects multiple distinct cognitive processes. *Psychonomic Bulletin and Review, 16*, 742–751.
- Ratcliff, R., & Van Dongen, H. P. A. (2011). A diffusion model for one-choice reaction time tasks and the cognitive effects of sleep deprivation. *Proceedings of the National Academy of Sciences, 108*, 11285–11290.
- Ratcliff, R., Van Zandt, T., & McKoon, G. (1999). Connectionist and diffusion models of reaction time. *Psychological Review, 106*, 261–300.
- Ratcliff, R., Thapar, A., & McKoon, G. (2001). The effects of aging on reaction time in a signal detection task. *Psychology and Aging, 16*, 323–341.
- Ratcliff, R., Cherian, A., & Segraves, M. (2003a). A comparison of macaque behavior and superior colliculus neuronal activity to predictions from models of simple two-choice decisions. *Journal of Neurophysiology, 90*, 1392–1407.
- Ratcliff, R., Thapar, A., & McKoon, G. (2003b). A diffusion model analysis of the effects of aging on brightness discrimination. *Perception & Psychophysics, 65*, 523–535.
- Ratcliff, R., Perea, M., Colangelo, A., & Buchanan, L. (2004a). A diffusion model account of normal and impaired readers. *Brain and Cognition, 55*, 374–382.
- Ratcliff, R., Thapar, A., & McKoon, G. (2004b). A diffusion model analysis of the effects of aging on recognition memory. *Journal of Memory and Language, 50*, 408–424.
- Ratcliff, R., Thapar, A., & McKoon, G. (2010). Individual differences, aging, and IQ in two-choice tasks. *Cognitive Psychology, 60*, 127–157.
- Ratcliff, R., Thapar, A., & McKoon, G. (2011). Effects of aging and IQ on item and associative memory. *Journal of Experimental Psychology: General, 140*, 46–487.
- Ratcliff, R., Love, J., Thompson, C. A., & Opfer, J. (2012). Children are not like older adults: A diffusion model analysis of developmental changes in speeded responses. *Child Development, 83*, 367–381.
- Roe, R. M., Busemeyer, J. R., & Townsend, J. T. (2001). Multialternative decision field theory: A dynamic connectionist model of decision-making. *Psychological Review, 108*, 370–392.
- Schmiedek, F., Oberauer, K., Wilhelm, O., Suß, H.-M., & Wittmann, W. (2007). Individual differences in components of reaction time distributions and their relations to working memory and intelligence. *Journal of Experimental Psychology: General, 136*, 414–429.
- Smith, P. L., & Ratcliff, R. (2004). The psychology and neurobiology of simple decisions. *Trends in Neurosciences, 27*, 161–168.

- Spaniol, J., Madden, D. J., & Voss, A. (2006). A diffusion model analysis of adult age differences in episodic and semantic long-term memory retrieval. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *32*, 101–117.
- Tuerlinckx, F., Maris, E., Ratcliff, R., & De Boeck, P. (2001). A comparison of four methods for simulating the diffusion process. *Behavior, Research, Instruments, and Computers*, *33*, 443–456.
- Vandekerckhove, J., & Tuerlinckx, F. (2008). Diffusion model analysis with MATLAB: A DMAT primer. *Behavior Research Methods*, *40*, 61–72.
- Voss, A., & Voss, J. (2007). Fast-dm: A free program for efficient diffusion model analysis. *Behavior Research Methods*, *39*, 767–775.
- Wagenmakers, E.-J. (2009). Methodological and empirical developments for the Ratcliff diffusion model of response times and accuracy. *European Journal of Cognitive Psychology*, *21*, 641–671.
- Wagenmakers, E.-J., Van Der Maas, H. L. J., & Grassman, R. P. P. (2007). An EZ-diffusion model for response time and accuracy. *Psychonomic Bulletin and Review*, *14*, 3–22.
- White, C. N., Ratcliff, R., Vasey, M. W., & McKoon, G. (2010). Using diffusion models to understand clinical disorders. *Journal of Mathematical Psychology*, *54*, 39–52.
- Wiecki, T. V., Sofer, I., & Frank, M. J. (2013). HDDM: Hierarchical Bayesian estimation of the drift-diffusion model in Python. *Frontiers in Neuroinformatics*, *7*, 1–10.
- Wong, K.-F., & Wang, X.-J. (2006). A recurrent network mechanism for time integration in perceptual decisions. *Journal of Neuroscience*, *26*, 1314–1328.
- Zeguers, M. H. T., Snellings, P., Tijms, J., Weeda, W. D., Tamboer, P., Bexkens, A., & Huizenga, H. M. (2011). Specifying theories of developmental dyslexia: A diffusion model analysis of word recognition. *Developmental Science*, *14*, 1340–1354.