Psychonomic Bulletin & Review
https://doi.org/10.3758/s13423-022-02200-2

BRIEF REPORT

The effect of speed-stress on driving behavior: A diffusion model analysis

Yonatan Vanunu[1] · **Roger Ratcliff**[1]

Accepted: 6 October 2022

Abstract

In everyday driving on the road, people are often required to make fast decisions that could compromise the accuracy of choices. We present a diffusion model analysis of the adjustments drivers make to the decision process under speed-stress. Participants operated a PC-based driving simulator while performing one of two decision-making tasks that required a driving action as a response to the stimulus. In a one-choice driving task, participants were asked to drive around a lead car when its brake lights were turned on. A two-choice driving task used a brightness-discrimination task in which participants were asked to drive to the left and back behind a lead car if there were more black than white pixels in a display and to the right and back if there were more white than black pixels. Speed-stress was operationalized by instructing drivers to respond as quickly as possible and by manipulating the distance drivers were required to maintain behind the lead car. Results showed the expected speed-accuracy tradeoff; however, the cost on accuracy in the two-choice task was relatively small. The model-based analysis showed that this was achieved by lowering the decision criteria and speeding up nondecision processes without disrupting components that produce evidence for the decision process. In fact, in the one-choice task, evidence accumulation rate in the speed-stress condition was found to be higher than in the accuracy-stress condition. We concluded that drivers were able to comply with speed-stress demands with relatively safe adjustments that imposed minimal costs on the accuracy of choices.

Keywords Driving · Speed-accuracy · Diffusion modeling · Reaction time · Decision-making

Introduction

Driving is an integral part of the day-to-day routine for many people, with the number of licensed drivers in the USA increasing from approximately 167 million in 1990 to 222 million in 2016 (Wagner, 2021). Consequently, there is a need to understand driving skills, and how they are affected by stresses to respond quickly that occur in normal driving. Previous research has shown that drivers' responses to a decelerating car were more acute (e.g., braking hard to a full stop) as the distance between the cars decreased (Wang et al., 2016). While these acute responses to unexpected events are crucial for avoiding collisions or minimizing damage (Harb et al., 2009), the type of response chosen by the driver might not always be the optimal one (Markkula et al., 2012). For example, Li et al. (2019) investigated which type of response – braking or steering – drivers are more likely to execute in response to different types of collision-hazards. They suggested that under extreme situations in which fast responses are stressed, choices for the appropriate response were based on a heuristic approach in which some of the problem's features are ignored – leading to fast responses but possibly more errors. In the current study, we used the *one-choice diffusion model* (Ratcliff & Van Dongen, 2011) and the *two-choice diffusion model* (Ratcliff, 1978; Ratcliff & McKoon, 2008; Wagenmakers, 2009) to examine the effect of *speed-stress* on the decision process during driving. In the two-choice task, there is tradeoff between speed and accuracy of the response with higher accuracy associated with longer response times (RTs) and lower accuracy associated with shorter RTs. We define speed-stress as demands that induce drivers to make fast responses, and we pit it against *accuracy-stress* in which drivers are encouraged to make accurate responses.

✉ Yonatan Vanunu
yyv1984@gmail.com

[1] The Ohio State University, 1835 Neil Avenue, Columbus, OH 43210, USA

Published online: 26 October 2022

According to the standard two-choice diffusion model shown in Fig. 1, noisy evidence is accumulated from a starting point z to one of two decision criteria 0 or a. The rate of evidence accumulation is called drift rate (v) and it represents the quality of evidence from the stimulus. The time it takes to reach one of the criteria is the decision time. Three representative paths for decision time are shown in Fig. 1: one leads to a fast correct decision, one to a slow correct decision, and one to an error. Within-trial variability (noise) in the decision process gives rise to right skewed RT distributions and error responses that occur when the process hits the wrong boundary by mistake. Consequently, lower drift rates produce longer RTs and more errors. The models also represent the time it takes to execute nondecision functions, such as stimulus encoding and motor planning, with a single parameter – nondecision time – that has a mean duration T_{er}. The decision and nondecision parameters are assumed to vary from trial to trial: drift rate is assumed to be normally distributed with standard deviation (SD) η; nondecision time and starting point are assumed to be uniformly distributed with range s_t and s_z, respectively. Finally, we represented the proportion of slow contaminant responses by a delay in processing with probability p_o (see Ratcliff & Tuerlinckx, 2002).

The one-choice diffusion model describes a process that is composed of decision and nondecision processes as in the two-choice model. However, evidence in the one-choice model is accumulated towards a single criterion a from a fixed starting point 0, which is not assumed to vary between trials (see Ratcliff & Van Dongen, 2011). Moreover, Ratcliff and Van Dongen (2011) have shown that there is a problem in identifiability in the one-choice model in that one of the model parameters needs to be fixed and then the others are identified. We chose to fix the between-trial variability in drift rate in our application of the one-choice model. See section A1 in the Appendix for more details about the fitting methods.

Many previous studies have used the diffusion model to examine the effect of speed-stress on the decision process in various cognitive tasks (e.g., Rae et al., 2014; Ratcliff, 2002, 2006; Ratcliff & Rouder, 1998; Ratcliff et al., 2001, 2003, 2004; Starns et al., 2012; see also Rinkenauer et al.,

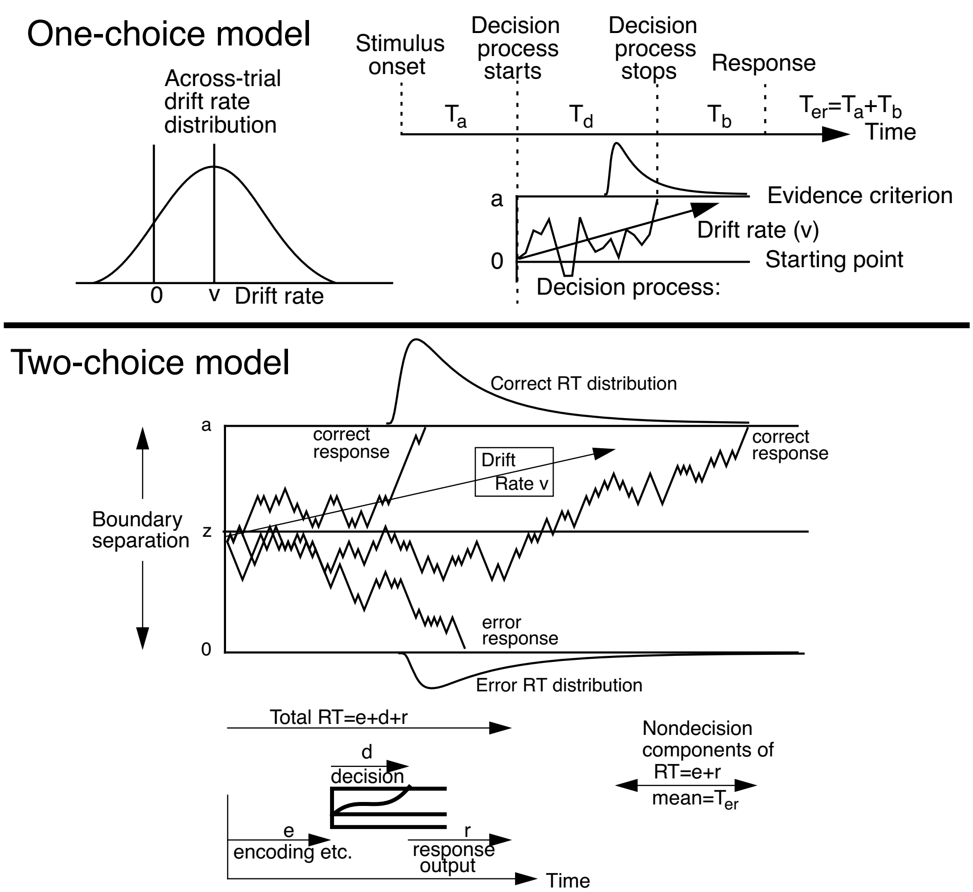

Fig. 1 An illustration of the one-choice and two-choice diffusion models. Across models, v represents the drift rate with normally distributed between-trial variability with SD η; a represents boundary separation; T_{er} represents nondecision time, which is assumed to distributed uniformly with range s_t. The two-choice model also specifies the starting point z, which is assumed to be distributed uniformly with range s_z

2004; Voss et al., 2004). However, results from these studies were not always consistent. That is, boundary separation was almost always higher under accuracy-stress than speed-stress conditions, but differences in nondecision time were smaller and less consistent (e.g., Ratcliff, 2006), and differences in drift rate occurred less often and were inconsistent across the type of task (e.g., Rae et al., 2014). Here we examined the effects on making decisions while driving.

Based on previous work, we outline three levels of speed-stress that modulate different components of the decision process: (i) low-stress results in lower boundary separation; (ii) medium-stress results in lower boundary separation and shorter nondecision time; (iii) large-stress results in lower boundary separation, shorter nondecision time, and lower drift rate (for a recent review, see Ratcliff & McKoon, 2022). Here we aim to test whether imposing speed-stress on making decisions while driving changes critical components of the decision process such as evidence accumulation (i.e., high-stress level). This question is important because a low drift rate for making decisions while driving would indicate lower evidence being used and hence greater potential for errors. For example, Starns et al. (2012) argued that under extreme speed-stress, people are likely to speed up nondecision processes to produce faster responses. In so doing, they might disrupt or reduce the amount of time spent on stimulus-encoding, producing lower-quality evidence (lower drift rates). Consequently, adjusting the time spent on stimulus encoding under acute speed-stress should reduce accuracy to a greater degree than the effect that would occur from adjusting boundary separation alone.

The one- and two-choice diffusion models have been previously used to examine changes in the components of the decision process during driving in response to experimental manipulations, such as imposing distractions or more difficult driving environments (Ratcliff, 2015; Ratcliff & Strayer, 2014; Ratcliff & Vanunu, 2022; see also Castro et al., 2019; Tillman et al., 2017). In these studies, participants were required to operate a PC-based driving simulator while performing a decision task at varying times during the driving task. In a one-choice task, participants were asked to drive around a lead car when its brake lights were turned on. This task was designed to mimic driving around a slowing vehicle in real driving and to parallel the *psychomotor vigilance task* (PVT), which measures participants' vigilance by asking them to press a button as quickly as possible when a stimulus is displayed (Dinges & Kribbs, 1991; Dinges & Powell, 1985; Ratcliff & Van Dongen, 2011). In a two-choice task (a *brightness-discrimination task*), a stimulus-patch of black and white pixels was displayed, and drivers were required to steer the car to the left or right (or drive around the lead car in other versions of the task) if the patch was bright or dark, respectively. This allows interactions of speed and accuracy, and components of decision-making to be examined.

Data from the one- and two-choice driving tasks were fitted by the one- and two-choice diffusion models, respectively. Results showed good fits and provided an interpretation of the behavioral effects in terms of the decision-making process. For instance, Ratcliff and Vanunu (2022) tested the effect of aging on the decision process in the one- and two-choice driving tasks. Findings showed that older adults were slower to respond in the one-choice task and made more errors in the two-choice task than young adults. These patterns were captured in the model by lower drift rates in older than young adults. Interestingly, differences in RTs between age groups were small because RT in real-world driving often has an upper limit – determined by the behavior of other drivers on the road, i.e., *traffic demands*. Therefore, to compensate for lower drift rates to fit traffic demands in the two-choice task, older adults adjusted the duration of the decision process by lowering the decision criteria. Hence, it seems that traffic demands imposed an *implicit* speed-stress that resulted in a similar adjustment of boundary separation to that found in cognitive tasks with a low speed-stress manipulation. This accounted for the small proportion of the reduced accuracy found in the older group's data.

The goal of our study is to examine which components of the decision process change in response to an *explicit* manipulation of speed-stress on decision-making during driving in young adults. We asked participants to operate a PC-based driving simulator while performing the one- and two-choice driving tasks. Drivers were asked to respond to a stimulus by driving around the lead car in the one-choice task and by steering the car to the adjacent lane and back in the two-choice task. We chose steering as the required response because in real-world driving situations, people often need to make fast decisions about changing lanes when selecting routes or avoiding obstacles. A speed-accuracy manipulation was implemented between blocks, in which participants were instructed to make responses either as quickly or as accurately as they could. Drivers were also required to keep a constant distance from the lead car, as might occur in real-world driving (and this was monitored by a research assistant sitting beside them). The required distance behind the lead car was manipulated to be shorter under the speed-stress than accuracy-stress conditions (90 ft vs. 120 ft). We assumed that a smaller distance between the cars would leave less time for the driver to execute a response – i.e., increasing speed-stress. The diffusion model analysis shows which components of the decision process are adjusted in order to conform to the speed-stress demands in both tasks.

Method

Participants

Twenty-three young adults (13 females, age: 18–25 years, M = 21.2 years) were recruited through fliers posted at The

Ohio State University. They were paid $12 per session for participation. An additional nine participants were recruited for course credits (six females). Two participants were excluded from the analysis due to an inability to perform the tasks. All participants were drivers with a mean of 4.5 years of experience.

Apparatus

The tasks were presented on a 15.6-in. Dell XPS L502SX laptop, with events sampled at a 16.67 ms sampling rate and a screen resolution of 1,600 × 900 pixels. STISIM Drive software version 2 was used to present the driving simulations in different landscapes. A Logitech Driving Force GT steering wheel with force feedback (http://www.logitech.com) and two pedals (accelerator and brake) were used to allow the participants to drive in the simulated environment.

Design and materials

The simulated driving environment in the one-choice driving task included two lanes in an open space highway during daytime. The simulator's dashboard included speed and RPM meters and a rear-view mirror (see Fig. 2, left panel). The driver's car and the lead cars were placed in the right lane. Drivers were asked to approach a lead car on each trial, but to keep a constant distance from it. When the driver achieved the required distance, the lead car "wobbled" left and right to indicate the onset of the trial. The main purpose of the lead car was to simulate traffic demands, which often requires drivers to keep a constant pace and distance from other drivers on the road. When the brake lights of the lead car turned on, the driver was required to steer the car to the left and drive around the decelerating car. When the lead car receded to the rear (as visible in the rear-view mirror), the driver was required to steer the car back to the right lane and speed up until a new lead car appeared. The time interval between the onset of the trial and the display of brake lights varied across trials from 2 s to 10 s in 2-s steps (Ratcliff, 2015).

The simulated driving environment in the two-choice driving task included three lanes of an interstate highway during daytime (Fig. 2, right panel). Both the driver's car and the lead car were placed in the middle lane. Between 0 s and 8 s (M = 4 s) after the onset of each trial, a stimulus patch of a 64 × 64 array of black and white pixels was displayed for 2 s between the two meters on the driver's dashboard and at the base of the lead car. The task was to steer the car into the right lane if the patch was bright (had more than 50% white pixels) and into the left lane if it was dark. Unlike the one-choice driving task, here the driver was not asked to drive around the lead car, but to drive the car into the appropriate lane and then drive it back to the middle lane behind the lead car. The probability of a pixel being white in the stimulus array was .57, .53, .47, or .43 (i.e., the *brightness* conditions). We chose values that in previous work gave accuracy values around 90% for the easier conditions and in the 70–80% range for the other conditions (e.g., Ratcliff, 2015). Two example patches from each brightness condition were shown to the driver at the beginning of the task to calibrate them. In both tasks, a speed-accuracy manipulation was implemented between blocks. Participants were instructed to respond either as quickly as they could or as accurately as they could. For the speed-stress condition, a message displayed at the beginning of the block asked the participants to respond as quickly as possible. For the accuracy-stress condition, a message asked the participant to respond "normally" as they would in light traffic in the one-choice driving task, and to respond as accurately as they could in the two-choice driving task. Throughout

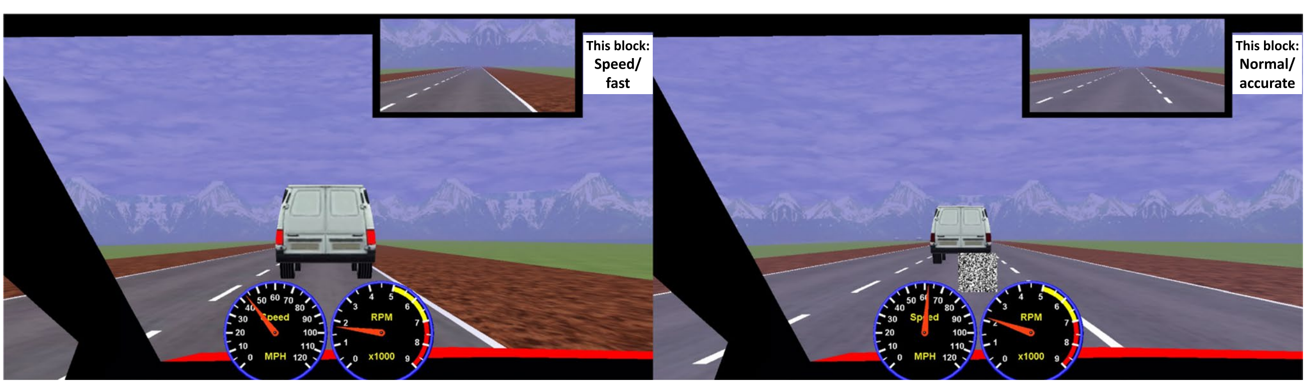

Fig. 2 Example screen shots of driving views from the two driving tasks. The left panel shows the one-choice driving task when the brake lights of the lead car turned red under the speed-stress condition. The right panel shows the two-choice driving task when a brightness-discrimination patch is displayed under the accuracy-stress condition. The stress-type condition (speed-stress vs. accuracy-stress) for the block of trials was displayed in the upper-right corner of the display

the session, the respective speed versus accuracy message appeared in the upper-right corner of the screen. In addition, we asked participants to keep a constant distance from the lead car throughout the trial, which was set to 95 ft for the speed-stress condition and 120 ft for the accuracy-stress condition. We assumed that a smaller distance should impose a greater stress to respond quickly in order to comply with traffic demands. RT was defined as the time between the stimulus onset (brake light or brightness-discrimination patch) and the time at which the driver started to steer the car sideways – i.e., the response. We used a linear interpolation of the sideways velocity to estimate the response time. The sideways velocity first increased and then became approximately constant for a short period of time as the car steered to the right or left. Linear interpolation from this relatively constant velocity provided an estimate of when the car began to turn, an estimate that was consistent across responses by the participant. Trials where no action was recorded (e.g., the driver remained in the middle lane and did not steer the car) were excluded from data analyses. Other details of the methods can be found in Ratcliff (2015).

Procedure

Participants were told they were about to drive in a PC-based simulated environment. In both tasks, they were asked to approach a lead car on the road until it wobbled, and to maintain this distance until stimulus display. The drivers were informed that using the brake pedal is unnecessary, as one could slow down by taking the foot off the gas pedal. To minimize potential dizziness or nausea during the driving tasks, the lights in the testing room were dimmed and subjects were encouraged to take breaks when needed. Finally, a research assistant monitored the participants throughout the session, making sure they complied with the instructions such as to maintain a fixed distance from the lead car, to respond as fast or as accurately as possible according to the stress-type condition, and to not drive off-road.

Overall, participants participated in four sessions that were 1 day apart. In each session, they carried out both tasks with 31 min allocated to the one-choice driving task and 19 min for the two-choice driving task. Each task started with three practice trials. The speed-stress and accuracy-stress conditions were manipulated between blocks, alternating in counterbalanced order across participants. In the one-choice driving task, participants carried out on average 13.8 speed-stress and 13.9 accuracy-stress blocks, and in the two-choice driving task they carried out on average 14.1 speed-stress and 14.3 accuracy-stress blocks. Each block consisted of 20 trials, although the last block in each session was often cut short due to time-limits.

Results

Behavioral results

For the one-choice data, we used a linear mixed-effects model with RT as the dependent variable, stress-type as a fixed factor, and participants as a random intercept effect. For the two-choice data, we used a linear and a probit mixed effects model with RT and accuracy as dependent variables, respectively. The fixed and random variables were as in the one-choice analysis, but with brightness as an additional fixed factor. Lower and upper RT cutoffs were set to 150 ms and 2,500 ms for the one-choice task, and to 400 ms and 2,500 ms for the two-choice task. On average, 2.6% and 1.6% of the responses of each participant were excluded from the one- and two-choice tasks, respectively. The results are displayed in Fig. 3.

First, we found a main effect for stress-type in both tasks, showing shorter RTs under the speed-stress than accuracy-stress conditions (one-choice: M_S = 509 ms, SD = 78 ms vs. M_A = 636 ms, SD = 92 ms; $\chi^2(1) = 521.8$, $p < .001$; two-choice: M_S = 815 ms, SD = 103 ms vs. M_A = 1,011 ms, SD = 130 ms; $\chi^2(1) = 18.1$, $p < .001$; Fig. 3, left panel). Second, we found a main effect of brightness in the two-choice task ($\chi^2(3) = 1121$ $p < .001$), showing faster responses to “easier” patches ($M_{.57}$ = 910 ms, SD = 143 ms and $M_{.43}$ = 848 ms, SD = 107 ms vs. $M_{.53}$ = 964 ms, SD = 114 ms and $M_{.47}$ = 929 ms, SD = 101 ms). An interaction effect between brightness and stress-type ($\chi^2(3) = 12.9$, $p = .004$) indicated that the effect of brightness was smaller under the speed-stress condition. This can be interpreted as a standard *scaling effect* (Ratcliff et al., 2000). That is, differences in mean RTs among conditions were smaller under speed-stress than accuracy-stress, because RTs have an absolute minimum value, while there is no theoretical maximum value (though practically, in driving and our tasks, the maximum should vary with traffic demands). Consequently, the range and variability of responses across brightness conditions was larger in the accuracy-stress condition (one-choice: range = 355 ms and SD = 91.5 ms; two-choice: range = 662 ms and SD = 130.3 ms) than in the speed-stress condition (one-choice: range = 323 ms and SD = 77.8 ms; two-choice: range = 479 ms and SD = 102.9 ms).

For accuracy in the two-choice task, we found a significant main effect for stress-type ($\chi^2(1) = 18.1$, $p < .001$) that indicated that on average, accuracy was higher under accuracy-stress (M = .86, SD = .05) than speed-stress (M = .84, SD = .05) conditions, although this difference was relatively small (i.e., only 2%). Moreover, a main effect for brightness showed that accuracy was higher for “easier” patches ($M_{.57}$ = .91, SD = .08 and $M_{.43}$ = .97, SD = .04 vs. $M_{.53}$ = .71, SD = .15 and $M_{.47}$ = .81, SD = .11; $\chi^2(3) = 1{,}121.3$, $p < .001$).

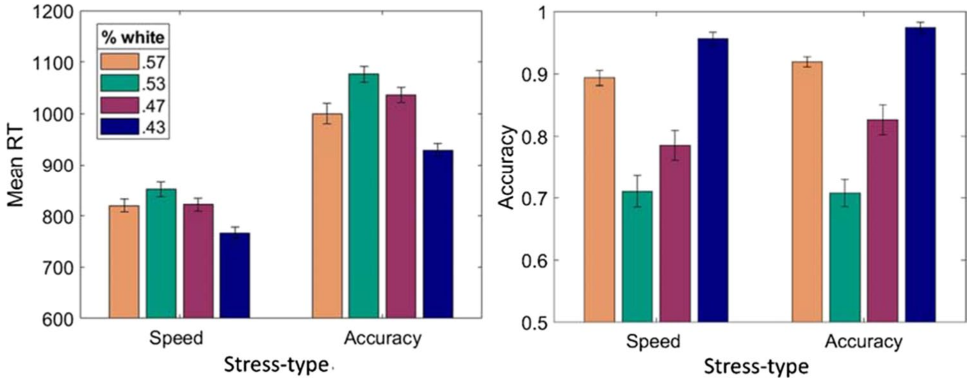

Fig. 3 The mean response times (RTs) for speed- and accuracy-stress and brightness conditions in the two-choice driving task (left panel), and the proportions of correct responses for the same conditions (right panel). Error bars correspond to the within-subjects standard error computed according to a normalization method (Cousineau, 2005)

We also found evidence for a contrast effect ($\chi^2(1) = 195.6$, $p < .001$), in which accuracy was higher for darker (M = .89, SD = .07) than brighter (M = .81, SD = .11) patches. This is because there was a smaller difference in contrast between the brightness of the patch and the relatively bright background (in simulated daytime). Finally, an interaction effect between brightness and stress-type ($\chi^2(3) = 6.2$, p = .013) showed that the effect of brightness on accuracy was smaller under the speed-stress condition, probably due to similar scaling effects we found in the RT data above.

Model fitting results

We fitted the one- and two-choice models to each participant and stress-type condition separately (i.e., all parameters were allowed to vary between stress-type conditions). Figure 4 shows cumulative RT distributions averaged over participants in the one-choice driving task (panel A), and RT quantiles for brighter and darker responses collapsed across participants in the two-choice task (panel B), both plotted against the respective model's predictions – showing a good fit to data (see A1 in the Appendix for more details about fitting methods). The mean parameters' values, the mean χ^2 goodness of fit values, and the number of participants with χ^2 less than the critical value, χ^2_c for each task are presented in Tables 1 and 2. The critical χ^2 values for each stress-type condition were 23.7 with 14 degrees of freedom in the one-choice model and 47.4 with 33 degrees of freedom in the two-choice model. Across models, the mean χ^2 values were below the respective critical values, and the majority of participants across models exhibited χ^2 values that were below the respective critical values.

Parameter values

We used paired-sample t-tests to examine the differences in parameter values as a function of the stress manipulation. The resulting t statistics, their significance levels and the effect sizes are presented in Table 3. Across tasks, boundary separation was significantly lower and nondecision time was significantly shorter under speed-stress than accuracy-stress conditions, accounting for the shorter RTs found under speed-stress in both tasks. Hence, it seems that participants produced faster responses by lowering the decision criteria and by speeding up their nondecision processes. Importantly, we found no differences in drift rates between stress-type conditions in the two-choice model – suggesting that speeding up nondecision processes under the current design did not disrupt stimulus-encoding. Therefore, the small reduction in accuracy rates we found in the two-choice data (2%) can be explained by a reduction in boundary separation alone.

Drift rates in the one-choice task were slightly higher in the speed- than accuracy-stress conditions, which stands in contrast to previous findings from similar speed-stress manipulations in two-choice designs (Rae et al., 2014; Ratcliff, 2002; Starns et al., 2012). Nevertheless, it is important to note that the simpler one-choice task was primarily designed to measure vigilance, which might be enhanced in response to speed-stress. By contrast, when drivers were asked to respond "normally" as they would in light traffic (i.e., accuracy-stress), their vigilance might have been reduced in comparison to the speed-stress condition – resulting in slightly lower drift rates.

Between-trial variability in nondecision time (s_t) was smaller in the speed-stress than accuracy-stress conditions across tasks, probably as a result of the scaling effects we found in the data (i.e., the smaller range of RTs under the speed-stress condition). The ratio z/a was significantly smaller ($t[29] = -3.57$, p = .001) under speed-stress (M = .456, SD = .082) than accuracy-stress (M = .511, SD = .097) conditions, and was significantly below .5 for the speed-stress condition ($t[29] = -2.93$, p = .006).

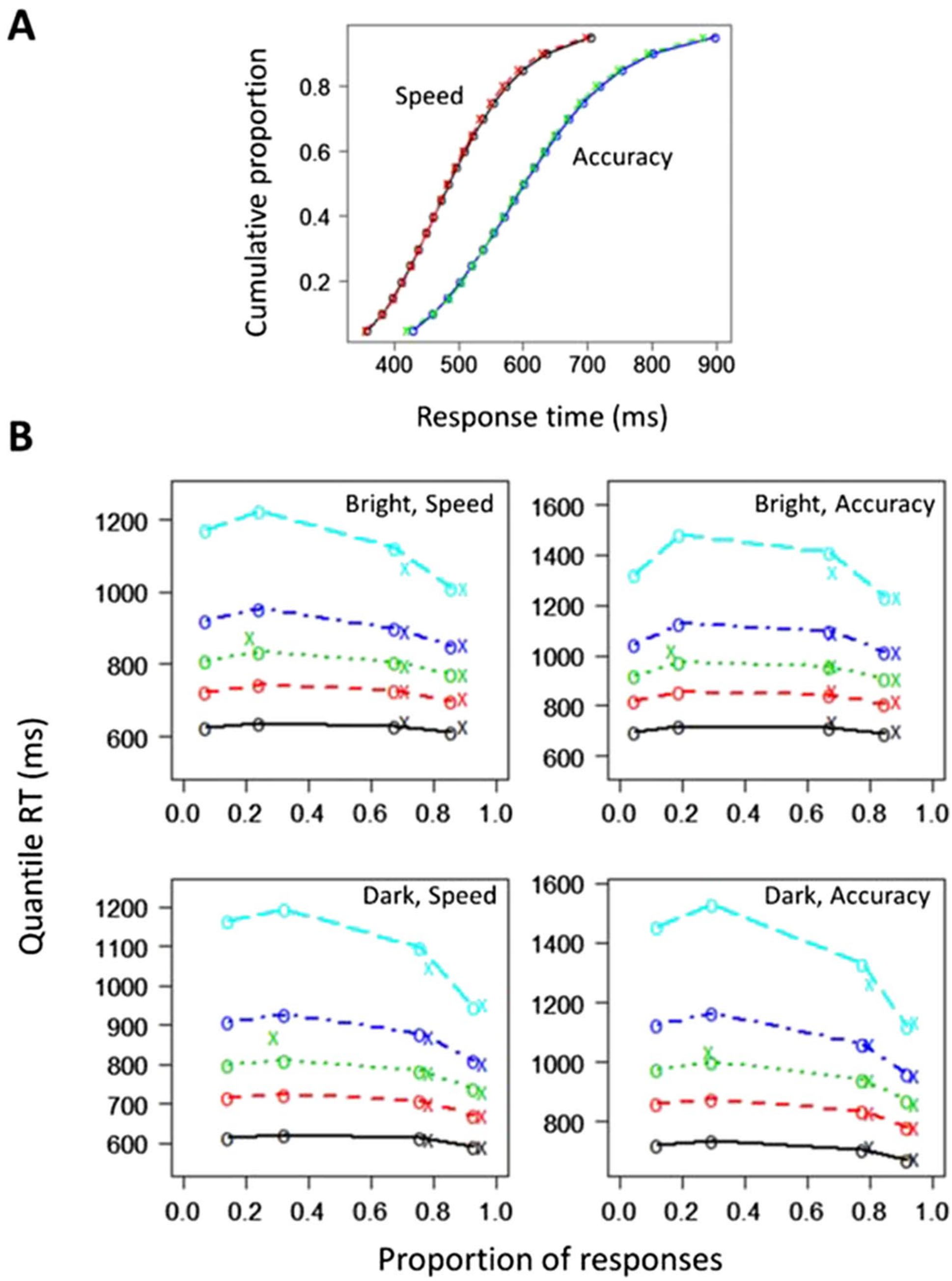

Fig. 4 **A** Cumulative response time (RT) distributions for each speed-stress condition, averaged over participants in the one-choice driving task. **B** Quantile-probability functions for each speed-stress condition, averaged over participants (The quantiles were first computed for each participant separately and then averaged across participants) in the two-choice driving task. 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 RTs in order from the bottom to the top are the .1, .3, .5, .7, and .9 quantiles. x represents the behavioral data and lines and o represents the theoretical fits of the diffusion models. When there are less than five observations for some of the participants, the median (green x) is plotted, and when some participants have no errors, nothing is plotted for that condition

Discussion

The current study presents a novel model-based analysis that examines the effect of stressing speed on the decision process during driving. In both the one- and two-choice tasks, drivers were required to make decisions about steering the car between lanes, which should reflect real-world driving decisions, such as avoiding obstacles on the road, selecting routes, or responding to the behavior of other drivers. The one-choice task provided a measure for vigilance and RT

Table 1 Mean parameter values across participants from the one- and two-choice diffusion models, fitted separately for the speed-stress and accuracy-stress conditions

Model	a	z	T_{er}	η	s_z	s_t	p_o	χ^2	$N(<\chi_c^2)$
One-choice speed	0.199	-	257	0.200	-	167	-	13.4	28/30
One-choice accuracy	0.238	-	308	0.200	-	240	-	15.3	27/30
Two-choice speed	0.119	0.055	613	0.178	0.047	277	.004	39.7	20/30
Two-choice accuracy	0.143	0.073	718	0.157	0.040	390	.003	35.4	24/30

a represents decision boundary separation; z represents the starting point; T_{er} represents the nondecision component of response time (in milliseconds); η represents the standard deviation in drift rate across trials; s_z represents range of the distribution of starting points (z); s_t represents range of the distribution of nondecision times; p_o represents proportion of contaminants; χ^2 averaged over participants represents goodness-of-fit; and $N(<\chi_c^2)$ represents the number of participants with χ^2 value below the critical value (out of N=30). The critical χ^2 values were 23.7 with 14 degrees of freedom and 47.4 with 33 degrees of freedom for each stress-type condition in the one- and two-choice models, respectively

Table 2 Mean drift rate values across participants from the one- and two-choice diffusion models

Model	$v_{.57}$	$v_{.53}$	$v_{.47}$	$v_{.43}$	V
One-choice speed					0.865
One-choice accuracy					0.811
Two-choice speed	0.318	0.154	-0.152	-0.384	0.252
Two-choice accuracy	0.277	0.120	-0.195	-0.390	0.246

$v_{.57}$ and $v_{.53}$ are for bright stimuli, and $v_{.47}$ and $v_{.43}$ are for dark stimuli; V represents the overall drift rate. For the two-choice driving task it is $(v_{.57}+v_{.53}-v_{.47}-v_{.43})/4$

and the two-choice task allowed speed-accuracy tradeoffs to be examined. In particular, we examined which model components change when participants are induced to respond as quickly as possible, as occurs in real-world driving situations. Critically, the model-based analysis allowed us to examine what type of adjustments to the decision process the participant employed under speed-stress, and how these adjustments might affect the accuracy of the decisions made.

Results from the behavioral analysis showed the expected reduction in RT under speed-stress across tasks. In the two-choice task, we found a speed-accuracy tradeoff – that is, shorter RTs and lower accuracy rates when speed was stressed. However, it seems that the current manipulation of speed-stress was not extreme enough to disrupt critical processes that give rise to evidence used in decision making. Specifically, participants in the two-choice task were able to reduce RT by 19% (196 ms) under the speed-stress condition, but with only a 2% reduction in accuracy.

The model-based analysis produced a good fit of the models to the data. It also provided an interpretation of how this behavior was achieved in terms of the models of the decision processes by showing which components of the underlying processes changed in response to speed-stress. Across models and tasks, we found lower boundary separation and a shorter nondecision time in speed-stress than accuracy-stress conditions. These results are consistent with previous findings from a similar speed-accuracy manipulation in cognitive tasks (e.g., Ratcliff, 2002, 2008; Ratcliff et al., 2001, 2003, 2004). Importantly, we found no differences in drift rates between the stress-type conditions in the two-choice model, which suggests that the small cost of speed-stress on accuracy obtained in the two-choice task can be explained by a reduction in decision criteria alone. This matches other studies that show that drift rates are usually not affected by speed-stress (e.g., Ratcliff, 2002), except under extreme cases of speed-stress in which stimulus-encoding is disrupted (Starns et al., 2012). By contrast, in the one-choice task we found slightly higher drift rates under speed-stress than accuracy-stress conditions. This could be because vigilance for detecting brakelights was enhanced under speed-stress and was lower when drivers were instructed to respond as they would in light traffic (accuracy-stress).

Table 3 The t statistics with 29 degrees of freedom, from the paired-sample t-tests for differences in the parameter values among speed-stress and accuracy-stress conditions. The Cohen's d effects sizes are displayed in brackets

Models	a	z	T_{er}	η	s_z	s_t	V	p_o
One-choice	**-3.11** (0.57)	**-**	**-3.39** (0.62)	-	-	**-6.18** (1.13)	**2.57** (0.47)	-
Two-choice	**-5.80** (1.06)	**-5.58** (1.02)	**-8.07** (1.47)	1.65 (0.30)	.80 (0.15)	**-5.95** (1.09)	.56 (0.10)	.34 (0.06)

Significant differences are marked in bold ($p < .05$)

Higher drift rates under speed-stress were also found in a study that used the one-choice diffusion model to examine the effect of speed-stress on estimating the *time to collision* (TTC) with other cars in a simulated driving-environment (Daneshi et al., 2020). Curiously, they also found that boundary separation was higher under time-pressure, which is counterintuitive considering the consensus in the literature in which lower boundary separation in response to speed-stress is obtained. Nevertheless, their work differed in many aspects to ours. For example, their model did not estimate nondecision time and its variability, and they did not control for the identifiability problem in the one-choice model, which could lead to inaccurate parameter estimation. Moreover, the pace of the driver's car was fixed, there was no stimulus-display that required an immediate response such as brake lights, and the dependent variable TTC was computed differently to ours. Therefore, it is difficult to compare the results of the two studies.

In the context of speed-stress levels, our manipulation imposed medium speed-stress that induced drivers to lower the decision criteria and to speed up nondecision processes. However, it is reasonable to assume that under more extreme situations, such as unexpected obstacles that require an immediate response or a smaller distance from the lead car, participants would be forced to make additional adjustments that would compromise accuracy to a greater degree. For example, previous studies have shown that in extreme cases of speed-stress in which the driver chose to swerve the car quickly to avoid collision with an obstacle, the direction of the swerve was often towards the conflict rather than away from it (i.e., "swerve-into-danger"; Hu & Li, 2017; Li et al., 2019; Malaterre et al., 1988; Weber et al., 2015). A diffusion model analysis might be able to explain how this counterintuitive response came about with respect to changes in the components of the decision process.

We concluded that participants were able comply with the current speed-stress demands with a relatively "safe" adjustment that imposed a minimal cost on accuracy. This was achieved by lowering the decision criteria and by reducing nondecision time without disrupting critical processes such as stimulus-encoding, which is responsible for the quality of evidence in the decision process.

Appendix

Fitting method

The one- and two-choice models were both fitted to each participant and stress-type condition separately. Because the one-choice model does not have an explicit solution for the distribution of response times (RTs) for a negative drift rate (generated from the left tail of the between-trial distribution of drift rate; see Fig. 1), we fitted the one-choice model by simulating a random walk approximation to the diffusion process (Ratcliff & Van Dongen, 2011). Each simulated condition used 20,000 iterations with a 0.5-ms step size (Tuerlinckx et al., 2001). The maximum RT in the simulation was set to 3,000 ms, and any RT that exceeded this boundary was set to this maximum value (this occurred 0.4% of the time). In the one-choice data, there is only one RT distribution, which makes it important to use as much distributional information as possible. Consequently, we fitted the one-choice model to 19 quantiles of the RT distribution (20 bins), with a step of .05 between quantiles (i.e., .05, .1, .15, etc.). The first and second quantiles in the one-choice model were grouped to produce more stable estimates of the leading edge of the RT distribution (by minimizing the effects of a few anticipations that produced extremely short RTs; see Ratcliff & Strayer, 2014). Because the one-choice model has an issue of parameter identifiability, we fixed η to 0.2 when fitting this model to data, as we felt it is a reasonable value for the current data set. For the two-choice model, we used a standard explicit solution to fit the data (see Ratcliff & Tuerlinckx, 2002). Five quantiles of the two RT distributions for correct and error responses (i.e., .1, .3, .5, .7 and .9; 6 bins for each distribution) were used to fit the two-choice model. In both models, we fixed the within trial SD to 0.1.

The parameters of the model were optimized by a simplex minimization routine, which searched for a set of parameters that produced the lowest chi-square value – calculated as $\Sigma(O–E)^2/E$ (Ratcliff & Tuerlinckx, 2002). The observed values (O) were calculated by multiplying the total number of observations by the proportions of responses between the data quantiles (e.g., .05 in the one-choice model). The expected values (E) were calculated by multiplying the total number of observations with the proportion of responses in the predicted RT distribution that laid between the data quantiles, predicted from the simulation routine (one-choice) or the explicit solution (two-choice). Contributions were computed separately for each condition (brightness) and for correct responses and error responses, and the values were added for an overall value of chi-square. For the one-choice model, the simplex minimization routine was restarted 18 times with a wide simplex round the parameters estimated from the prior fit. To examine the goodness-of-fit of the models, the average chi-square value across participants in each stress-type condition was compared to a respective critical value $\left(\chi_c^2\right)$. To represent the goodness-of-fit at the individual level, we counted the number of participants in each group and task with χ^2 smaller than the critical value (i.e., $N[<\chi_c^2]$).

Funding This work was supported by funding from the National Institute on Aging (Grant numbers R01-AG041176 and R01-AG057841).

References

Castro, S. C., Strayer, D. L., Matzke, D., & Heathcote, A. (2019). Cognitive workload measurement and modeling under divided attention. *Journal of Experimental Psychology: Human Perception and Performance, 45*(6), 826–839.

Cousineau, D. (2005). Confidence intervals in within-subject designs: A simpler solution to Loftus and Masson's method. *Tutorial in Quantitative Methods for Psychology, 1*(1), 42–45.

Daneshi, A., Azarnoush, H., & Towhidkhah, F. (2020). A one-boundary drift-diffusion model for time to collision estimation in a simple driving task. *Journal of Cognitive Psychology, 32*(1), 67–81.

Dinges, D. F., & Kribbs, N. B. (1991). In T. H. Monk (Ed.), *Sleep, Sleepiness and Performance* (pp. 97–128). Wiley.

Dinges, D. F., & Powell, J. W. (1985). Microcomputer analyses of performance on a portable, simple visual RT task during sustained operations. *Behavior Research Methods, Instruments, & Computers, 17*, 652–655.

Harb, R., Yan, X., Radwan, E., & Su, X. (2009). Exploring precrash maneuvers using classification trees and random forests. *Accident Analysis & Prevention, 41*(1), 98–107.

Hu, M., & Li, Y. (2017, October). Drivers' avoidance patterns in near-collision intersection conflicts. In; *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)* (pp. 1-6). IEEE.

Li, X., Rakotonirainy, A., & Yan, X. (2019). How do drivers avoid collisions? A driving simulator-based study. *Journal of Safety Research, 70*, 89–96.

Malaterre, G., Ferrandez, F., Fleury, D., & Lechner, D. (1988). Decision making in emergency situations. *Ergonomics, 31*(4), 643–655.

Markkula, G., Benderius, O., Wolff, K., & Wahde, M. (2012). A review of near-collision driver behavior models. *Human Factors, 54*(6), 1117–1143.

Rae, B., Heathcote, A., Donkin, C., Averell, L., & Brown, S. (2014). The hare and the tortoise: emphasizing speed can change the evidence used to make decisions. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 40*(5), 1226–1243.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review, 85*(2), 59–108.

Ratcliff, R. (2002). A diffusion model account of response time and accuracy in a brightness discrimination task: Fitting real data and failing to fit fake but plausible data. *Psychonomic Bulletin & Review, 9*(2), 278–291.

Ratcliff, R. (2006). Modeling response signal and response time data. *Cognitive Psychology, 53*(3), 195–237.

Ratcliff, R. (2008). Modeling aging effects on two-choice tasks: response signal and response time data. *Psychology and Aging, 23*(4), 900–916.

Ratcliff, R. (2015). Modeling one-choice and two-choice driving tasks. *Attention, Perception, & Psychophysics, 77*(6), 2134–2144.

Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: theory and data for two-choice decision tasks. *Neural Computation, 20*(4), 873–922.

Ratcliff, R., & McKoon, G. (2022). *Re-examining the effects of speed-accuracy instructions with a diffusion model based analysis*. [Manuscript submitted for publication].

Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological Science, 9*(5), 347–356.

Ratcliff, R., & Strayer, D. (2014). Modeling simple driving tasks with a one-boundary diffusion model. *Psychonomic Bulletin & Review, 21*(3), 577–589.

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*(3), 438–481.

Ratcliff, R., & Van Dongen, H. P. (2011). Diffusion model for one-choice reaction-time tasks and the cognitive effects of sleep deprivation. *Proceedings of the National Academy of Sciences, 108*(27), 11285–11290.

Ratcliff, R., & Vanunu, Y. (2022). The effect of aging on decision-making while driving: A diffusion model analysis. *Psychology and Aging, 37*(4), 441–455.

Ratcliff, R., Spieler, D., & Mckoon, G. (2000). Explicitly modeling the effects of aging on response time. *Psychonomic Bulletin & Review, 7*(1), 1–25.

Ratcliff, R., Thapar, A., & McKoon, G. (2001). The effects of aging on reaction time in a signal detection task. *Psychology and Aging, 16*(2), 323–341.

Ratcliff, R., Thapar, A., & McKoon, G. (2003). A diffusion model analysis of the effects of aging on brightness discrimination. *Perception & Psychophysics, 65*(4), 523–535.

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*(4), 408–424.

Rinkenauer, G., Osman, A., Ulrich, R., Müller-Gethmann, H., & Mattes, S. (2004). On the locus of speed-accuracy trade-off in reaction time: inferences from the lateralized readiness potential. *Journal of Experimental Psychology: General, 133*(2), 261–282.

Starns, J. J., Ratcliff, R., & McKoon, G. (2012). Evaluating the unequal-variance and dual-process explanations of zROC slopes with response time data and the diffusion model. *Cognitive Psychology, 64*(1-2), 1–34.

Tillman, G., Strayer, D., Eidels, A., & Heathcote, A. (2017). Modeling cognitive load effects of conversation between a passenger and driver. *Attention, Perception, & Psychophysics, 79*(6), 1795–1803.

Tuerlinckx, F., Maris, E., Ratcliff, R., & De Boeck, P. (2001). A comparison of four methods for simulating the diffusion process. *Behavior Research Methods, Instruments, & Computers, 33*(4), 443–456.

Voss, A., Rothermund, K., & Voss, J. (2004). Interpreting the parameters of the diffusion model: An empirical validation. *Memory & Cognition, 32*(7), 1206–1220.

Wagenmakers, E. J. (2009). Methodological and empirical developments for the Ratcliff diffusion model of response times and accuracy. *European Journal of Cognitive Psychology, 21*(5), 641–671.

Wagner, I. (2021, April 15). *Car Drivers - Statistics & Facts*. Statista. Retrieved May 13, 2021, from https://www.statista.com/topics/1197/car-drivers/

Wang, X., Zhu, M., Chen, M., & Tremont, P. (2016). Drivers' rear end collision avoidance behaviors under different levels of situational urgency. *Transportation Research Part C: Emerging Technologies, 71*, 419–433.

Weber, S., Blum, K., Ernstberger, A., & Färber, B. (2015). Standard reactions–driver reactions in critical driving situations. *Procedia Manufacturing, 3*, 2489–2496.

Open science statement The data and the R code used to analyze this data are available via the Open Science Framework at (https://osf.io/864et/). Fitting packages for the diffusion model are available from Voss and Voss (2007). This study was not preregistered.