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A Cognitive Modeling Perspective

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Human Decision-Making in High-Risk Driving Scenarios: A Cognitive Modeling Perspective

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***Abstract*—In mixed traffic, one of the challenges for autonomous driving technology is how to safe and socially acceptable interaction with human-driven vehicles (HVs). Understanding human cognitive processes during decision-making in interactions with other road users is crucial for enhancing the smooth execution of driving tasks by autonomous vehicles (AVs). This paper proposes a cognitive model of the driver's cumulative information processing based on drift-diffusion model (DDM). By incorporating the initial decision biases, drift rate, and boundary (depending on the initial speed and gaps between ego vehicle and surrounding users) into the existing DDM, our model captures the integrated interaction between individual drivers and other road users. Classic emergency collision avoidance scenarios were constructed based on a driving simulation platform. Our cognitive model accurately described human decision-making in high-risk scenarios, identified key qualitative and quantitative input variables affecting the driver's cognitive processes, and quantified the safety thresholds of the driver's cumulative information processing. Results can support the personalized modeling of human drivers' cognition and facilitate safe and effective interactions between HVs and AVs.**

Keywords— Autonomous vehicle decision-making; driver risk cognition; driving simulator study; high-risk environments.

I. Introduction

In real-world traffic, human drivers use non-verbal communication, such as gestures and motion cues, to negotiate effectively and make socially compatible decisions in complex and congested scenarios [1]. The characteristics of driver perception, decision-making, and control directly impact vehicle stability and safety. Driver risk cognition involves the subjective understanding of potential risks in traffic, guiding behavioral decisions [2]. Despite sensory noise, drivers prioritize critical information through cognitive filtering, leading to reasonable choices. Although significant progress has been made in autonomous driving in recent years, autonomous vehicles (AVs) still face challenges in decision-making conflicts in high-risk interaction scenarios, such as left-turn problems and cut-in timing dilemmas [3]. To be accepted by human road users, AVs are expected to possess human-like decision-making and judgment capabilities, emphasizing operating safely and possessing human-like decision-making and judgment capabilities. This involves integrating human social preferences (altruism, egoism, cooperation, competition) and demonstrating proactive responsiveness and social intelligence. Understanding dynamic interactions among human drivers in complex traffic can help AVs emulate exemplary driving behaviors, enabling them to make reasonable and socially compatible decisions, crucial for success in interaction-intensive and safety-critical environments [4].

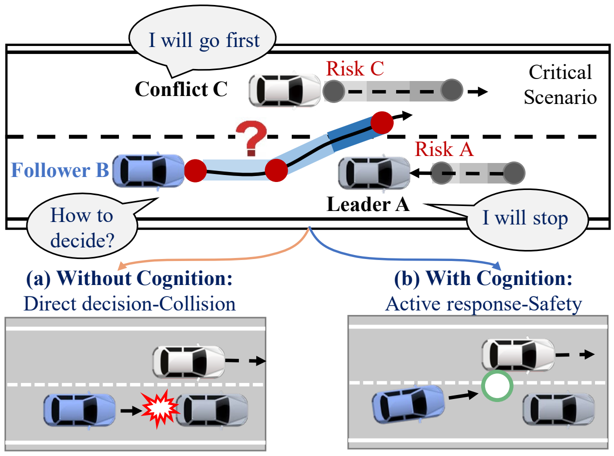

Fig. 1. Illustration of the vehicle decision dilemma in a critical scenario. (a) Without cognition, follower B only observes other vehicles' actions, ignoring the judgment of situation risks, causing collisions. (b) With cognition, follower B actively decides based on situation risks in response to the other vehicles' actions.

As illustrated in Fig. 1, when AVs lack human-like cognitive processes, their decisions can diverge from human driving logic, increasing the risk of errors and collisions. Therefore, incorporating human-like risk cognition in AVs is essential for enhancing safety, particularly in high-risk scenarios [5]. We expect to develop a risk cognition-based interactive decision-making model, which supports AVs in operating similarly to humans by characterizing and predicting acceptable safety thresholds and threshold-based reasonable decision-making behavior in high-risk scenarios. However, current driver risk cognition and behavior models, often provide qualitative descriptions but lack quantitative metrics to capture the dynamic complexity of drivers' responses to varying risk levels, resulting in incomplete or inaccurate predictions. Additionally, these models do not account for individual differences in drivers' risk cognition, leading to generalized assumptions that may not apply to diverse driver groups. These limitations hinder their effectiveness in capturing complex interactive behaviors [6]. To address this gap, this paper introduces human cognition-inspired modeling and decision-making for AVs, particually in high-risk scenarios. Our contributions are as follows:

- Based on extensive experimental data analysis, we developed a cognitive evidence accumulation model for drivers and calibrated its parameters. This model quantitatively characterizes human risk cognition and decision-making behaviors.
- By mining data from driving simulator-based studies, we refine and analyze key variables influencing drivers' behaviors in high-risk scenarios and capture the comprehensive interactions between drivers and other road users.
- By employing the drift-diffusion model (DDM) based on cumulative information processing, we can explain the decision-making principles of humans from a cognitive perspective in high-risk scenarios.

The rest of this paper is organized as follows. Section 2 introduces the literature review, and Section 3 describes the data collection method of driver behavior experiments based on the driving simulator. In Section 4, we illustrate the modeling of human behavioral decision-making. The performance of the proposed method and the conclusion of this study are summarized in Sections 5 and 6.

II. Literature Review

Assessing driving scenarios from an expert driver's perspective can better enable AVs to adapt their interactive behaviors to complex dynamic traffic. Methods for understanding and predicting human behavior in complex systems can be categorized into three types [5]: game theory-based reasoning models, learning-driven models, social field and force models, and cognitive models.

Game theory-based reasoning models offer a robust framework for analyzing strategic interactions among rational agents, where each participant's actions impact the outcomes of others [7]. In modeling driver cognition based on game theory, it is essential to dynamically consider the safety and comfort of the vehicle while also accounting for the intentions and behaviors of surrounding road users. Hence, driver decisions result from multi-vehicle game interactions, leading to optimal strategy outputs. Bayesian dynamic models are also commonly used in behavior reasoning [8]. Darius et al. [9] proposed a probabilistic prediction framework based on dynamic Bayesian networks (DBN), considering multi-vehicle interactions in traffic environments and using context-aware motion models at intersections to define driver interaction behaviors. By combining prior knowledge with observed data, game theory-based models provide a probabilistic framework for predicting and deciding driver behavior [10]. However, their reliance on rational behavior assumptions limits their real-world applicability. Moreover, these models often neglect descriptions of drivers' risk perceptions, and decision-making complexity increases with more agents and strategies.

Learning-driven models leverage data mining and knowledge acquisition from large volumes of driving data through deep neural networks (DNN) and convolutional neural networks (CNN) [11]. These methods can identify complex patterns from extensive datasets. Sharifzadeh et al. [12] used deep Q-networks for deep reinforcement learning to study lane-changing and overtaking patterns on highways but did not address vehicle safety and used simple simulation scenarios. While these models effectively manage complex high-dimensional data, they typically function as "black boxes," limiting interpretability and providing no insights into the underlying mechanisms of drivers' risk cognition and decision-making behaviors.

Potential field and social force models explore the influence of social context and the presence of others on individual behavior. Commonly used to describe pedestrian dynamics and crowd behavior, these models assume individuals experience attraction and repulsion forces from others and environmental factors, guiding their movement and interactions. Recent research integrates human-social interaction concepts into autonomous vehicle-human vehicle (AV-HV) interactions. Algorithms for behavior prediction and multi-agent reinforcement learning (MARL) frameworks incorporating social value orientation (SVO) have been developed [13]. These models capture the impact of social interactions on behavior but may oversimplify complex personal decision-making processes by reducing them to force-based models.

Cognitive models aim to explain human cognitive processes, drawing from cognitive psychology and neuroscience to simulate how humans perceive, think, and decide [14]. By modeling cognitive functions such as attention, memory, and learning, they help understand and predict human behavior. The DDM, a classic information accumulation model with diffusion signals [15], elucidates driver decision-making mechanisms. This model has been recently utilized for describing driver decision-making in left-turn and overtaking scenarios [16], addressing gaps between cognitive decision models and naturalistic driving studies [17]. This method, based on the classic DDM, considers drivers' gap acceptance decisions and simulates the underlying cognitive processes, offering a real-time prediction approach and revealing the cognitive mechanisms. By simulating human cognitive processes, these models can predict and explain human behavior in ways closely aligned with actual behavior. This capability is crucial in designing automated systems such as AVs.

III. High-Risk Scenario Driver Cognition Database

We conducted extensive driving simulator experiments, focusing on high-risk scenarios to capture human cognitive and decision-making behaviors. The experiments involved participants navigating simulated environments with various risk factors, such as sudden obstacles, unpredictable traffic patterns, and high-density traffic conditions.

A. Participants

A total of 58 drivers participated in the experiment, all holding valid driving licenses and having normal or corrected-to-normal vision. They completed a basic information questionnaire and a subjective-style questionnaire. Specifically, as shown in Table 1, the content includes name, age, driving experience, and annual average driving mileage, while the subjective style questionnaire covered driving accidents and driving style (cautious, normal, radical). Data from 54 (mean age = 36.5 years; standard deviation [SD] =8.37; range=22-55; 8 females and 50 males) were analyzed.

Table 1. Demographic variables for collected drivers.

	Age /*Year*	Driving years/*Year*	Average driving time/*Hour*	Mileage/ *Kilometer*
Mean	36.50	12.10	39.29	23731.43
SD	8.37	7.10	38.24	19213.04

B. Experimental Platform

A driving simulation platform is regularly used to study the influence of driving performance on conflict risk. As displayed in Fig. 2, the simulator hardware includes the Logitech G29 steering wheel and accelerator, brake pedal kit, driving simulation environment display device, and a linear motion base with one degree of freedom (pitch). The full-size cabin features a realistic operation interface, environmental noise, motion simulation, a digital video playback system, and a vehicle dynamics simulation system. The environment is projected with a 300-degree field of view at 1400 × 1050 resolution, including rearview mirrors. Simultaneously, supporting software for driving scenario design, virtual traffic environment simulation, and virtual road modeling is provided, which can realize the functions of complex road construction, traffic flow generation, and traffic control.

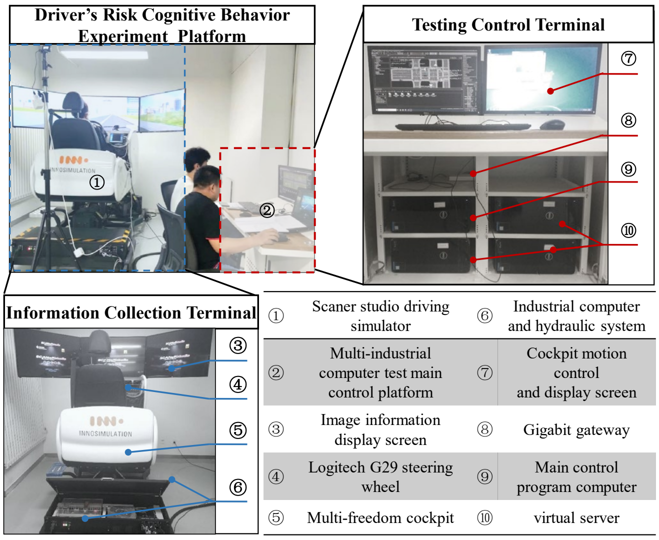

Fig. 2. Driving simulator platform.

C. Experimental Design and Analysis

Considering vehicle conflicts with the environment and road users, our designs were based on accident types reported by the NHTSA and GES. The most common hazardous scenarios include rear-end collisions (29%), intersection crossings (24%), road departures (19%), and lane changes (12%) [18]. Therefore, in this study, we designed comparative experiments considering rear-end collisions with leading vehicle's emergency braking, as shown in Fig. 3. The multi-stage driver behavior experiment adheres to a risk cognition paradigm, encompassing pre-experiment calibration, in-experiment recording, and post-experiment processing. Specifically, in this experiment, we consider three vehicles, leader A, follower B, and conflict C. Specifically, leader A and conflict C are environmental vehicles with a constant velocity of 80 km/h defined by the driving simulator, and follower B is the follower B driven by a driver, performs normal commute driving in highway. The experimental scenario setting details are shown in Table 2. When leader A suddenly activates the emergency brake with a deceleration of -8 m/s², conflict C is still driving in the left lane ahead at a constant speed of 80km/h, while driver participants of follower B need to decide whether to change lanes by steering left or apply emergency brakes and stop in response to the emergency brake of the leader A. Notably, throughout the experiment, the driver of follower B was unaware of the behavior settings of leader A and conflict vehicle C, allowing for a more authentic capture of reaction time, deceleration, and other behavior characteristics under unexpected conditions.

Table 2. Experimental scenario setting.

Parameters	Initial speed/ *km/h*	Initial headway (d)/*m*	Process speed/ *km/h*	Trigger conditions	End states
Leader A	80	100	80(CV)	d=40m, A=-8m/s^2 (EB)	Stop
Follower B	0	0	80-120		Stop/ LC
Conflict C	8	-1	80(CV)	-	80 km/h

Note: CV means constant velocity, EB is the emergency brake, and LC represents lane changing.

D. Data Processing and Key Variable Extraction

In the cognitive response process, the appearance of a stimulus is defined as the reference zero moment for reaction time. Key variables include cognitive reaction time (CRT), braking reaction time (BRT), speed adjustment time (SAT), etc. CRT is the interval from the first appearance of a risk source (or traffic disturbance) in a scenario to when the driver first notices it. BRT is defined as the time from the occurrence of a traffic disturbance to when the driver initiates an active response, measuring deceleration response capability in high-risk scenarios. SAT is the duration from the start of braking to the vehicle reaching maximum deceleration. Specifically, CRT reflects the driver's risk recognition ability based on experience and habits, while BRT shows the driver's control ability during emergency avoidance. Using CRT as a basis, the final decision-making phase determines the timing for obstacle avoidance measures.

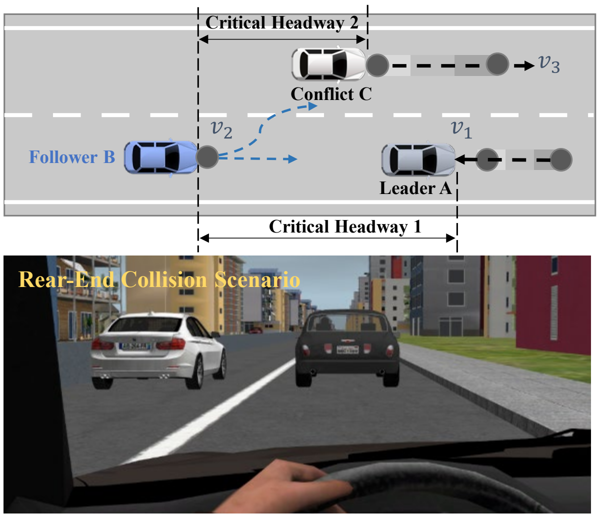

Fig. 3. The rear-end collision scenario with leading vehicle braking.

The decision involves two main options: steer or brake. These maneuvers respond to external stimuli and address current traffic conditions. Decision-phase variables include the maximum deceleration during braking, minimum time-to-collision (TTC), collision avoidance measures (steer/brake), maximum steering angle, average braking depth, etc. In the driver risk cognition experiment, as illustrated in Fig. 4, data processing of drivers' behavior in the critical scenario reveals significant differences in decision-making among drivers under the same traffic conditions. Drivers accumulate information first, using cognitive reaction time as a reference to determine the timing of decision-making behaviors, influencing outcomes of collisions or safety. Therefore, studying the differences in key variables during decision-making can reflect their varying risk cognition abilities.

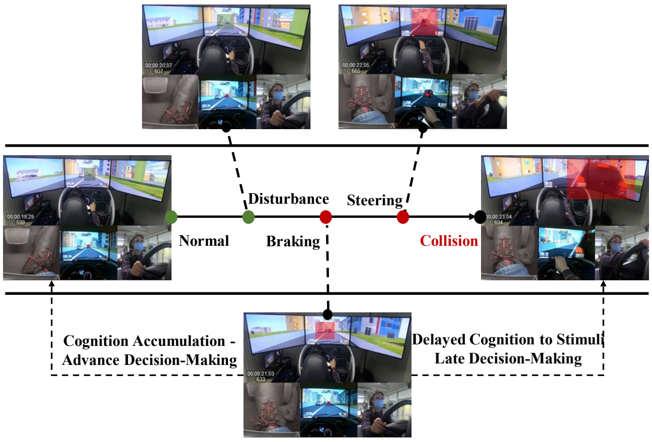

Fig. 4. Spatiotemporal distribution of decision-making behaviors in critical scenarios.

IV. Drift-Diffusion Modeling

The DDM quantitatively describes the information accumulation-decision process, where the brain accumulates noisy, uncertain information until a threshold is reached, prompting a decision. This model, based on stochastic drift-diffusion theory and integrating cognitive psychology and neuroscience, explains how drivers make decisions in complex scenarios [15]. Analyzing our dataset with this framework can help interpret participants' behaviors and response times.

A. *Drift Diffusion Model*

In Fig. 5, the baseline outputs for decision strategies 1 and 2 correspond to the threshold values C and -C, representing the driver's decision criteria. If there is a pre-decision bias influenced by prior knowledge, the starting point shifts upward or downward; without prior influence, it starts at zero. The drift rate determines the speed of the driver's risk response and braking decision, while the reaction time describes the duration of the decision-making process.

The drift-diffusion process mathematically represents the underlying psychological dynamics and multifactorial influences involved in the driver's decision-making strategies (risk response behaviors). It explains how choices are made during the output of multiple decision strategies. Compared to other models, the DDM comprehensively describes the entire sequence of driver behavior, from attention search and cognitive response to decision and control. Therefore, DDM is applied to mathematically express the information accumulation process in the driver's risk cognition and reactive decision-making.

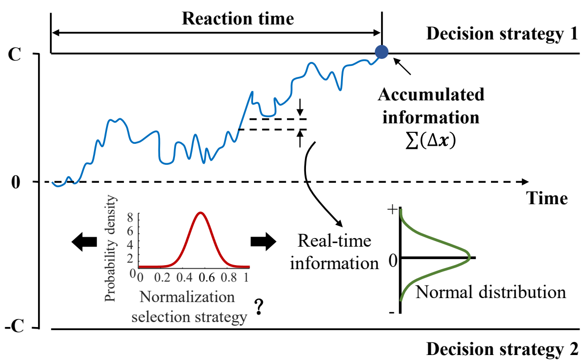

Fig. 5. The illustration of the drift-diffusion model.

In the drift-diffusion process, each strategy has a threshold indicating the required information accumulation before responding. Driver uncertainty introduces noise, meaning the accumulation direction may vary at any moment. This model elucidates how different decisions arise from accumulated information over time. As shown in Fig. 5, using information accumulation and evolution in the search phase as input and cognitive reaction time as the reference for information accumulation, DDM determines the timing for implementing avoidance measures in the decision-making process.

In this study, we construct the DDM to investigate the decision-making process of human drivers in the rear-end collision scenario. Specifically, we will focus on the process that starts when leader A brakes ($t = 0$), and ends when follower B decides to either steer or brake. The main components of the DDM established in this study, drift rate, boundary, initial bias, and non-decision time, are as follows.

1) *Drift Rate*

The drift rate $g(t)$ represents the average rate of evidence accumulation over time. It reflects the speed and direction of the decision-making process. In this study, $g(t)$ is considered as a function of the initial speed of the follower B: v_0, the time headway between follower B and leader A: $h^f(t)$, the distance between follower B and leader A: $s^f(t)$, the time headway between follower B and conflict C: $h^l(t)$, and the distance between follower B and conflict C: $s^l(t)$. The distances, $s^f(t)$ and $s^l(t)$ are measured as the bumper-to-bumper distance between the two vehicles. As shown in Equations (1) and (2), the time headways, $h^f(t)$ and $h^l(t)$, are obtained by dividing the distances $s^f(t)$ and $s^l(t)$ by the speed of follower B: $v(t)$.

$$h^f(t) = \frac{s^f(t)}{v(t)} \tag{1}$$

$$h^l(t) = \frac{s^l(t)}{v(t)} \tag{2}$$

We propose three drift rate formats (shown in Equations (3)-(5). $\alpha > 0$, $\beta > 0$, $\delta > 0$, $\kappa > 0$, $\gamma > 0$, and $\theta > 0$ are free parameters.

$$g(t) = \alpha(h^l(t) + \beta s^l(t) + \delta h^f(t) + \kappa s^f(t) + \gamma v_0 - \theta) \tag{3}$$

$$g(t) = \alpha(h^f(t) + \kappa s^f(t) + \gamma v_0 - \theta) \tag{4}$$

$$g(t) = \alpha(h^l(t) + \beta s^l(t) + \gamma v_0 - \theta) \tag{5}$$

2) *Boundary*

The boundary $b(t)$ represents the level of evidence required to make the decision. When the accumulated evidence reaches either the upper or lower boundary, a decision is made in favor of the corresponding option. Like formats of drift rate, the boundary is also defined as a function of v_0, $h^f(t)$, $s^f(t)$, $h^l(t)$, $s^l(t)$, but utilizes the SoftMax function. As shown in Equations (6)- (8), we propose three boundary formats. $b_0 > 0$, $k > 0$, $\beta > 0$, $\delta > 0$, $\kappa > 0$, $\gamma > 0$, $\tau > 0$ are free parameters to be calibrated.

$$b(t) = \pm \frac{b_0}{1 + e^{-k(h^l(t) + \beta s^l(t) + \delta h^f(t) + \kappa s^f(t) + \gamma v_0 - \tau)}} \tag{6}$$

$$b(t) = \pm \frac{b_0}{1 + e^{-k(h^f(t) + \kappa s^f(t) + \gamma v_0 - \tau)}} \tag{7}$$

$$b(t) = \pm \frac{b_0}{1 + e^{-k(h^l(t) + \beta s^l(t) + \gamma v_0 - \tau)}} \quad (8)$$

3) Initial Bias

The initial bias, denoted as Z, represents the starting point of the evidence accumulation process. A negative value of Z indicates an initial bias towards the "Brake" decision, while a positive value suggests a bias towards the "Steer" decision. In this study, we consider two formats for the initial bias: a constant value C_Z (Equation (9)) and a SoftMax function of the initial speed of follower B, v_0 (Equation (10)). $C_Z > 0$, $b_0 > 0, b_z > 0, v > 0$ are free parameters. We acknowledge that other factors also influence a driver's initial bias when making decisions, such as vehicle characteristics and the driver's experience. However, to simplify our modeling approach, we have only considered the driver's initial speed as a single indicator. In future research, we plan to incorporate more complex factors into our model.

$$Z = C_Z \quad (9)$$

$$Z = \frac{2b_0}{1 + e^{-b_z(v_0 - v)}} - b_0 \quad (10)$$

4) Non-Decision Time

The non-decision time t^{ND} represents the time taken by processes that are not directly related to the decision-making process itself. These processes include stimulus encoding, motor response execution, and any other processes that occur before or after the actual evidence accumulation. In this study, we assume a Gaussian distributed non-decision time shown in Equation (11). $\mu^{ND} > 0$ and $\sigma^{ND} > 0$ are free parameters to be estimated.

$$t^{ND} \sim N(\mu^{ND}, \sigma^{ND}) \quad (11)$$

5) Drift Diffusion Model Formulation

The formulation of the DDM is shown in Equation (12) [19], where $x(t)$ represents the evidence at time t, Positive values of $x(t)$ support the decision to "Steer," while negative values favor the decision to "Brake". $g(t)$ is the drift rate for the evidence accumulation defined in Equations (3)-(5). $\varepsilon(t)$ is the random noise added to the evidence. Through the combination of various formats of drift rate, boundary, initial bais, and non-decision time, we explore 14 different formats of the DDM to comprehensively analyze the decision-making process in the rear-end collision scenario.

$$\frac{dx(t)}{dt} = g(t) + \varepsilon(t) \quad (12)$$

B. Model Identification and Comparison

By combining various forms of the drift rate, boundary, and initial bias mentioned above, we obtained a total of 14 different DDMs. Among them, the parameter estimation failed for the combinations of Equations (5), (7), (9), (11) and Equations (4), (6), (10), (11). Therefore, only the remaining 12 DDM forms are compared and analyzed in this study (as shown in Table 3). Table 4 summarizes the free parameters in the DDMs established in this study. All 12 DDMs were programmed and calibrated using the PyDDM framework [20].

V. Results

In this section, we will analyze the modeling results. First, the accuracy of the 12 models will be examined. The models that best fit the dataset will then be selected. Next, using the well-fitting models, the drivers' decision-making process in the rear-end collision scenario will be interpreted from the cognitive perspective.

Table 3. Summary of drift-diffusion model.

Model index	Drift rate	Boundary	Initial bias	Non-decision time
M1	(3)	(6)	(9)	(11)
M2	(3)	(8)	(9)	
M3	(3)	(7)	(9)	
M4	(5)	(6)	(9)	
M5	(4)	(6)	(9)	
M6	(5)	(8)	(9)	
M7	(4)	(8)	(9)	
M8	(4)	(7)	(9)	
M9	(3)	(6)	(10)	
M10	(3)	(8)	(10)	
M11	(3)	(7)	(10)	
M12	(4)	(6)	(10)	

Table 4. Free parameters in the DDMs.

Model index	Parameters	Number of parameters
M1	$\alpha, \beta, \delta, \kappa, \gamma, \theta, b_0, k, \tau, C_Z, \mu^{ND}, \sigma^{ND}$	12
M2	$\alpha, \beta, \delta, \kappa, \gamma, \theta, b_0, k, \tau, C_Z, \mu^{ND}, \sigma^{ND}$	12
M3	$\alpha, \beta, \delta, \kappa, \gamma, \theta, b_0, k, \tau, C_Z, \mu^{ND}, \sigma^{ND}$	12
M4	$\alpha, \beta, \delta, \kappa, \gamma, \theta, b_0, \tau, C_Z, \mu^{ND}, \sigma^{ND}$	11
M5	$\alpha, \beta, \delta, \kappa, \gamma, \theta, b_0, \tau, C_Z, \mu^{ND}, \sigma^{ND}$	11
M6	$\alpha, \beta, \gamma, \theta, b_0, \tau, C_Z, \mu^{ND}, \sigma^{ND}$	9
M7	$\alpha, \beta, \kappa, \gamma, \theta, b_0, \tau, C_Z, \mu^{ND}, \sigma^{ND}$	10
M8	$\alpha, \kappa, \gamma, \theta, b_0, \tau, C_Z, \mu^{ND}, \sigma^{ND}$	9
M9	$\alpha, \beta, \delta, \kappa, \gamma, \theta, b_0, k, \tau, \mu^{ND}, \sigma^{ND}, b_z, v$	13
M10	$\alpha, \beta, \delta, \kappa, \gamma, \theta, b_0, k, \tau, \mu^{ND}, \sigma^{ND}, b_z, v$	13
M11	$\alpha, \beta, \delta, \kappa, \gamma, \theta, b_0, k, \tau, \mu^{ND}, \sigma^{ND}, b_z, v$	13
M12	$\alpha, \beta, \delta, \kappa, \gamma, \theta, b_0, k, \tau, \mu^{ND}, \sigma^{ND}, b_z, v$	13

A. Model Formats Determining

The accuracy of the 12 DDMs will be analyzed by comparing the model's predicted response times and decision-making probabilities with the actual data in the dataset.

Fig. 6 shows the comparison results between the model-predicted response times and the actual data. Due to the wide distribution range of initial speeds of follower B, from 17.82m/s to 26.82m/s, the actual data was divided into four groups based on the initial follower B speed, with the median initial follower B speeds for each group being 19.56 m/s, 22.10 m/s, 23.32 m/s, and 25.80 m/s, respectively. The black dots and error bars represent the mean and standard deviation of the response times for the steer and brake decisions in the real data, while the colored lines represent the predicted response times for the two decisions by the DDMs. We expect the model predictions to pass through or be as close as possible to the mean response times in the real data and capture the trend of response times as the initial speed changes. From Fig. 6, for the steer decision, seven models, namely M1, M2, M3, M6, M8, M9, M10, and M11, can fit well. These models all pass through the distribution range of the response times in the real data and capture the decreasing trend of the steer decision response time with the initial speed. For the brake decision, only three models, M9, M10, and M11, can fit well. The models pass through the distribution range of response times in real data and reproduce their variation, with a sharp decrease in the initial speed range of 22 m/s to 24 m/s.

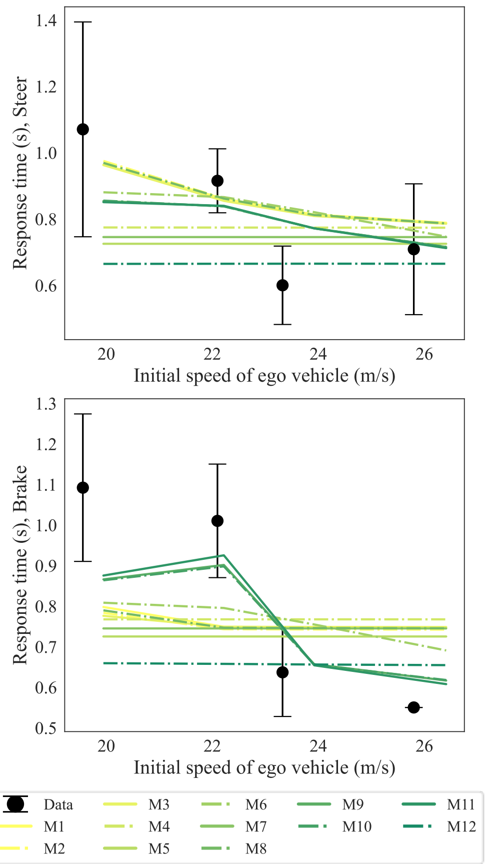

Fig. 6. Comparison of predicted response times from 12 DDMs with the actual response times in the dataset.

Fig. 7 shows the comparison results between the model-predicted cumulative response time probability and the actual data for both steer and brake decisions at various initial follower B speeds. In the real data, for both steer and brake decisions, the response times generally decrease with increasing initial speed. The response times for follower B's initial speeds of 19.56 m/s and 22.10 m/s are similar, and the response times for initial speeds of 23.32 m/s and 25.80 m/s are also similar. When the initial speed is lower, there is no significant difference in response times between steer and brake decisions. However, when the initial speed is higher, the response time for brake decisions is notably shorter than for steer decisions. Comparing the remaining small graphs, it can be observed that the trends in the cumulative probability shown by the three models, M9, M10, and M11, are similar to the trends in the original data shown in the large graph. The cumulative probabilities for steer and brake decisions at different initial speeds predicted by the other models are mostly clustered together and do not exhibit the trends seen in the actual data.

By comparing Fig. 6 and Fig. 7, it can be concluded that the three models, M9, M10, and M11, fit the actual data relatively well. The parameters for the three models are as follows:

M9: $\alpha = 1.09, \beta = 0.57, \delta = 0.00, \kappa = 1.00, \gamma = 1.59, \theta = 79.75, b_0 = 0.60, k = 0.95, \tau = 5.43, \mu^{ND} = 0.61, \sigma^{ND} = 0.17, b_z = 0.09, \nu = 14.71.$

M10: $\alpha = 1.22, \beta = 0.50, \delta = 0.00, \kappa = 0.92, \gamma = 1.43, \theta = 72.12, b_0 = 0.60, k = 1.30, \tau = 0.23, \mu^{ND} = 0.61, \sigma^{ND} = 0.17, b_z = 0.08, \nu = 14.32.$

M11: $\alpha = 1.21, \beta = 0.49, \delta = 0.00, \kappa = 0.84, \gamma = 1.40, \theta = 68.75, b_0 = 0.61, k = 0.90, \tau = 2.26, \mu^{ND} = 0.60, \sigma^{ND} = 0.16, b_z = 0.09, \nu = 15.50.$

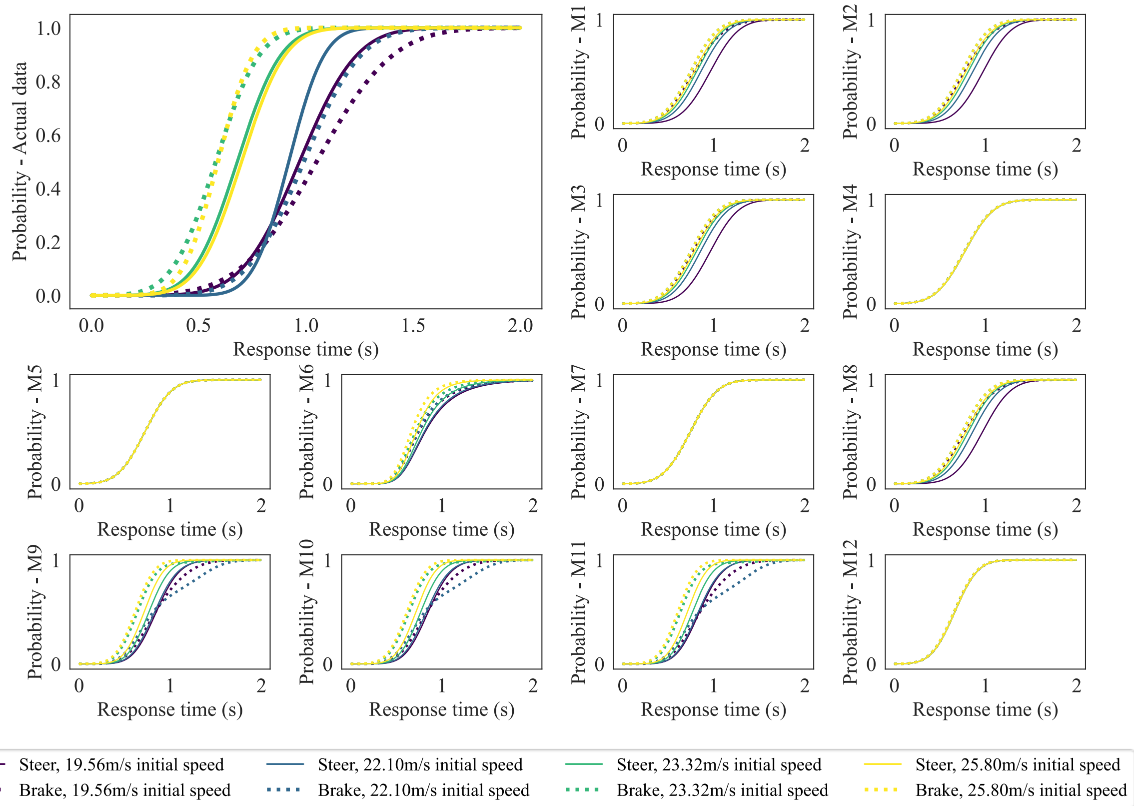

Fig. 7. Comparison of predicted cumulative response time probability between the data and the 12 DDMs.

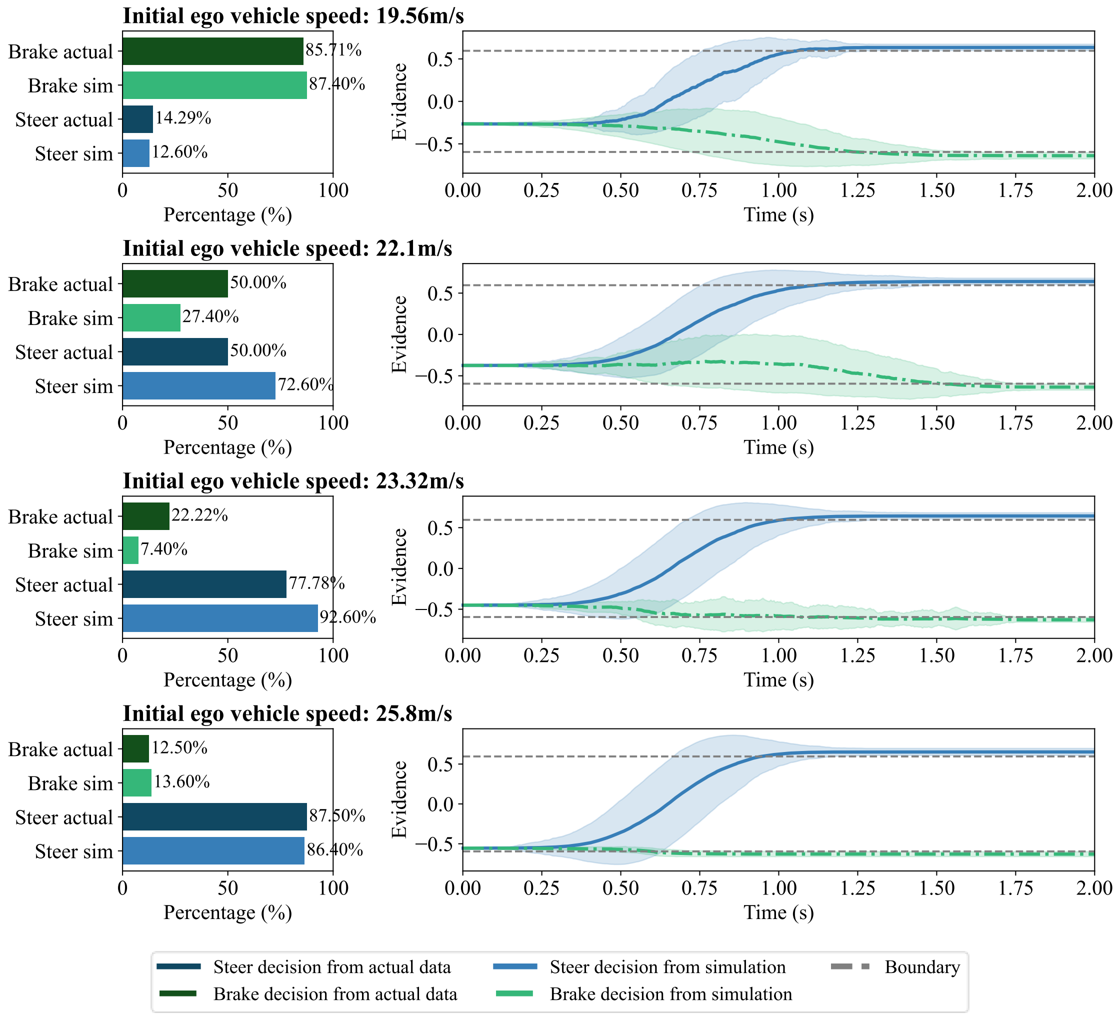

Fig. 8. Drivers' decision-making analysis at different initial speeds from a cognitive perspective predicted by M9. The left column shows the ratio of brake and steer decisions comparison between actual data and M9 predicted results. The right column illustrates the information accumulation process for both brake and steer decisions.

The most appropriate form of the DDM model for the front-emergency-braking scenario can be summarized as follows. For the drift rate, it is necessary to incorporate the initial speed of follower B and the distances to both the front and conflict Cs in the model. For the boundary, whether to include the distances to both the front and conflict Cs is not crucial. Regarding the initial bias, models that consider the initial speed of follower B are superior to those that do not.

B. Decision-Making Process Interpreting

In this section, we will interpret the driver's decision-making process from a cognitive perspective. We use M9, one of the models with better accuracy, to simulate decision-making in the front-emergency-braking scenario. We set up four groups of follower B speeds defined in the previous section: 19.56 m/s, 22.10 m/s, 23.32 m/s, and 25.80 m/s. Since the DDM model includes random factors, such as $\varepsilon(t)$ and t^{ND}, we conducted 1000 simulations for each initial speed group to eliminate the influence of random factors. Specifically, Fig. 8 shows the simulation results using M9. The left column represents the percentage, i.e. probability, of choosing steer and brake decisions at different initial speeds. The decision-making probability from actual data and simulation results are both presented. The right column visualizes the evidence accumulation process over time at different initial speeds of follower B. The blue and green lines represent the accumulation process of evidence $x(t)$ for steer and brake, respectively. The gray dashed lines represent the boundaries that trigger steer and brake decisions. When the evidence $x(t)$ accumulates to either the steer or brake boundary, the driver will make the corresponding decision.

From the left column of Fig. 8, when the initial speed is relatively low, drivers tend to choose to make a brake decision when faced with an emergency brake by leader A. As the initial speed increases, the probability of choosing the brake decision gradually decreases, while the probability of choosing the steer decision increases. When the initial speed is relatively high, facing an emergency brake by leader A, the time required to reduce the speed of follower B through braking is longer. Therefore, drivers will not choose to brake but instead make an immediate steer decision to respond. It could also be found that the M9 has a promising fit for the actual data. The decision-making probabilities predicted by the M9 are close to probabilities from the actual data.

From the right column of Fig. 8, the accumulation of evidence goes through two stages when making decisions. (i) Non-decision period: Receiving information about the emergency brake of leader A, during which the evidence does not change over time. From the fitting results of t^{ND}, it is known that this process takes about 0.6s. (ii) Evidence accumulation period: The driver begins to think about the information of leader A's emergency brake and determines whether to take steer or brake measures to respond. When the initial speed is relatively low, the response time required for drivers to make steer and brake decisions is similar. As the speed increases, the response times for both steer and brake decisions decrease, but the decrease in brake response time is more drastic. At this time, the driver will first judge whether there is a suitable opportunity to reduce the speed of the follower B by braking. If so, they will immediately make a brake decision. If not, the driver will choose an opportunity to make a steer decision.

VI. Conclusion

This paper introduces a cognitive model based on the driver's cumulative information processing and drift-diffusion decision-making, to capture driver behavior in high-risk scenarios. Key variables influencing driver cognition and decision-making are extracted from the driving simulator study. By integrating initial decision biases dependent on speed, the model effectively replicates human cognitive and decision-making behaviors in high-risk scenarios. Extensive simulation data analyses confirm the model's ability to identify key variables influencing driver risk cognition and quantify safety thresholds. The findings enable accurate modeling and prediction of individualized driver risk cognition and decision-making, enhancing driving safety and efficiency. The application of this model in autonomous driving technology promises to simulate human social intelligence, enhancing the adaptability of AVs to real driving conditions. Future work will focus on applying the model to AVs to achieve their safe and efficient interactive decision-making.

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