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Keywords: mixed-flow traffic, car-following behavior, driving simulator, string stability, parameter estimation

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Abstract—Connected and autonomous vehicles (CAVs) and human-driven vehicles (HDVs) will inevitably coexist on roads in the future, creating mixed-flow traffic. The heterogeneous car-following (CF) behavior of HDVs can degrade the control performance of CAVs and introduce inefficiencies in CAV operations. To address these challenges, it is necessary to comprehend HDV CF behavior in mixed-flow traffic. This driving simulator-based study investigates HDV CF behavior in mixed-flow traffic under three different CAV control settings (string-stable, string-unstable, and HDV-like). The effects of traffic congestion level and demographic characteristics on CF behavior are also considered. Statistical analysis and CF model calibration, based on trajectory data collected from 72 participants in driving simulator experiments, are performed to examine the impacts of these factors on string stability, traffic efficiency, and safety. Then, online parameter estimation is conducted to illustrate the time-varying desired time headway, and sensitivity to spacing and speed variations (i.e., CF behavior evolution). Additionally, analysis of post-experiment interview results and eye-tracking data show that the string-stable CAV control setting is preferred by most HDV drivers, but can trigger driver distraction. The results also provide insights for CF behavior prediction and the optimal mixed platoon formation to enhance CAV benefits for traffic flow.

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I. INTRODUCTION

ADVANCES in vehicle automation and communication technologies enable the development of connected and autonomous vehicles (CAVs). Through intelligent control algorithms and situational awareness provided by the communications capability, the longitudinal control of CAVs can improve traffic efficiency [1], [2], dampen traffic oscillations [3], [4], enhance safety [5], [6], and reduce energy consumption [7], [8]. However, prior to full autonomy, human-driven vehicles (HDVs) will inevitably coexist with CAVs on roads in the near-term future, creating mixed-flow traffic. CAV longitudinal control in mixed-flow traffic seeks to mitigate the HDV-initiated disturbances, which can be categorized into three groups: (i) reactive car-following (CF) control strategy, (ii) robust control strategy, and (iii) state-prediction-based control strategy. The reactive CF control strategy reacts to the disturbance propagated by the immediate predecessor HDV based on the corresponding sensor measurement to achieve safe and efficient CAV trajectories [9], [10]. The robust control

strategy seeks to mitigate the worst possible case (e.g., the largest speed and/or spacing fluctuations from HDVs) to bound CAV trajectories within prespecified ranges [11], [12]. State-prediction-based control strategy uses the predicted state information of multiple predecessor HDVs to enhance proactiveness so as to achieve desired performance of string stability, safety, and efficiency [13], [14]. However, most existing studies adopt CF models calibrated using trajectory data containing only HDV-following-HDV operations to model HDV behavior. This can be unrealistic in mixed-flow traffic, as HDVs can display different CF behavior when following autonomous vehicles (AVs) and CAVs [15], due to the different CF behavior of AVs/CAVs. Using unrealistic HDV behavior in developing CAV control can reduce the expected control performance in real-world operations. Moreover, heterogeneity and randomness in HDV behavior can also compromise the control performance of CAV platoons [5], [16]. Hence, to improve CAV control performance in mixed-flow traffic, it is essential to gain a better understanding of HDV CF behavior.

To study the CF behavior of HDVs under mixed-flow traffic, some studies in the literature have used field experiments in which real vehicles are used in test tracks and/or public roads to obtain human driving data. Zhao et al. [16] conduct a two-vehicle experiment to study HDV CF behavior when following an HDV or an AV with or without identifiable features. They find that the HDV exhibits different CF behavior when following AVs, and the spacing and speed variations of HDVs are dependent on drivers' trust in AVs. Rahmati et al. [17] conduct a three-vehicle platoon experiment where HDVs drive as the platoon lead and the platoon tail, with an AV/HDV in the middle. The platoon lead executes a trajectory obtained from the NGSIM dataset [18] to simulate real-world driving. Analyzing the CF behavior of the tail HDV, they find that drivers feel more comfortable when following an AV than an HDV as reflected by the smaller spacing and reduced concerns about collisions. Based on the same dataset, Mahdinia et al. [19] articulate the potential benefits of the HDV-following-AV scenario compared to the HDV-following-HDV scenario as: (i) HDV exhibits lower driving volatility and crash risk, and (ii) speed differences and fuel consumption are lower.

Driving simulator studies have been used to simulate the driving experience in a controlled environment to collect human-driving data. However, they have not been used to

analyze driver CF behavior in mixed-flow traffic, and focus on specific HDV driving aspects. Ramezani-Khansari et al. [20] study the effects of age, gender, and desired speed on HDV CF behavior by comparing with the calibrated General Motor CF model. They find that: (i) gender and desired speed level influence CF behavior, while age does not, (ii) increasing desired speed level will decrease the time headway, and (iii) women maintain larger spacing between vehicles compared to men. Calvi et al. [21] investigate human CF performance after switching from automated control to manual control in a harsh braking event, and find that collision probability is higher under such switches. Ali et al. [22] provide downstream traffic information (e.g., speed and spacing of predecessor vehicles) to drivers, and suggest that connected technologies help drivers to maintain larger time-to-collision, thereby improving safety.

While field experiments can provide realistic data, managing equipment, test tracks, and safety-related liability issues can be expensive, resource-intensive, and challenging. Further, such experiments are limited to the specific contexts and characteristics for which data is collected, precluding the ability to test variations in multiple real-world factors. Also, ambient vehicles not considered in the experimental design can impede data collection and compromise data quality. These issues can be solved in a driving simulator setting, where the simulated driving environment can be fully controlled, and no real collisions will occur. However, a driving simulator study using a desktop-based driving simulator (with a single monitor, steering wheel, and gas/brake pedals) lacks ecological validity, and hence, compromises experimental validity and data quality. More importantly, when analyzing the characteristics of HDV CF behavior, existing field experiments and driving simulator studies have not incorporated the traffic congestion level, CAV control setting, and driver demographic characteristics (e.g., age, gender, annual mileage, driving aggressiveness, trust in autonomous driving) together. Failing to consider these factors simultaneously will significantly restrict the comprehension of HDV CF behavior in mixed-flow traffic. Further, the evolution of CF behavior when following a CAV for a certain period in mixed-flow traffic has also not been studied. If not properly addressed, these gaps will jeopardize the transition from mixed-flow traffic to full autonomy, as CAVs developed based on inaccurate HDV CF behavior will inevitably cause undesired control performance in the real world.

To address the aforementioned research gaps, this study uses a high-fidelity full-cab driving simulator (Fig. 1(a)) to obtain human CF data in mixed-flow traffic. Fig. 1(b) shows the CF scenario used in this study, where the ego HDV (orange circle) follows the lead vehicle (blue oval) and three predecessor CAVs (green triangles) with prespecified control settings in the leftmost lane with no lane-change maneuvers. To provide a comprehensive understanding of HDV CF behavior in mixed-flow traffic, the study includes two independent variables: (i) the control setting of the predecessor CAVs, and (ii) the traffic congestion level. It considers three control settings for predecessor CAVs: string-stable (SS), string-unstable (SU), and HDV-like. The SS and SU CF behavior are modeled using the Constant Time Headway-Relative Velocity-Relative Acceleration (CTH-RV-RA) model [4]. Two sets of parameters are used to produce the SS and SU control settings of the predecessor CAVs. The HDV-like CF behavior is modeled

using the Intelligent Driver Model (IDM) with default parameter settings [23]. Four types of trajectories are incorporated in the lead vehicle to simulate traffic congestion level. They include free-flow traffic, mild congestion (free-flow speed with occasional acceleration/deceleration perturbations), and heavy congestion (stop-and-go traffic). The lead vehicle trajectories also include cyclical patterns to enable the analysis of CF behavior evolution. The detailed design of lead vehicle trajectories will be discussed in the experimental design section.

Four behavioral variables are considered to evaluate HDV CF behavior. The first is the string stability norm, which illustrates the capability of drivers to dampen speed fluctuations. The second is the percentage of overshoot/undershoot, which measures driver overreaction to sudden acceleration/deceleration from the predecessor CAVs. The third is the spacing between vehicles, which links to traffic efficiency under specific scenarios. The fourth is time-to-collision (TTC), which represents safety performance.

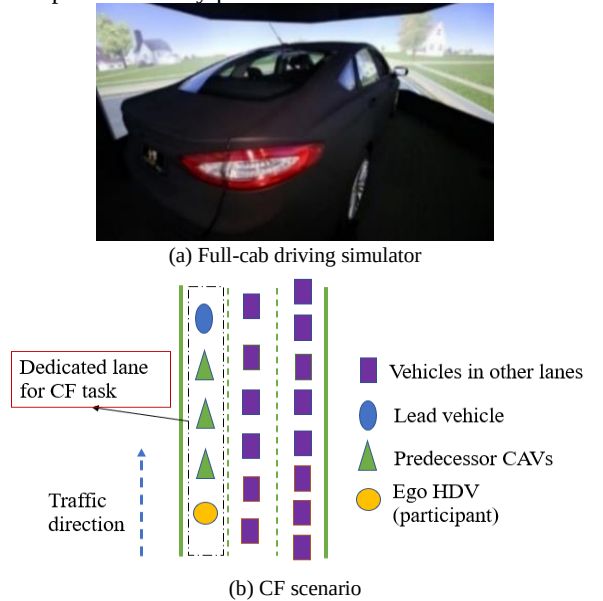


Fig. 1. Driving simulator and CF scenario

To analyze the variations of HDV CF behavior, statistical analyses (repeated measures ANOVA, mediation analysis) are performed on the behavioral variables, and HDV CF models are calibrated based on the CTH-RV model (simplified CTH-RV-RA model without the relative acceleration term) using a particle filter (PF) [24]. The results show that drivers display different desired time headways (i.e., time headways to be maintained in CF process), sensitivity to spacing and speed, and capabilities to dampen speed fluctuations, under different predecessor CAV control settings, congestion levels, and demographic characteristics. Then, an extended Kalman filter (EKF) [25] is applied to perform online parameter estimation to illustrate drivers' time-varying CF behavior and gradually attenuated capabilities for dampening speed fluctuations. Eye-tracking data and post-experiment interview results show that though the SS CAV is the most preferable option, it makes drivers gaze elsewhere instead of focusing on the predecessor vehicle (i.e., causes distracted driving).

The contributions of this study are two-fold. First, to the best of our knowledge, this is the first study to holistically investigate the variability in HDV CF behavior in mixed-flow

traffic under the impacts of predecessor CAVs, traffic congestion, and demographics, which can facilitate the development of more realistic models to accurately describe HDV actions in mixed-flow traffic. Second, we provide insights into the CF behavior evolution and the trade-offs between string stability and safety in HDV CF behavior, which can be used to design effective CAV control methods to overcome HDV-related challenges in mixed-flow traffic, and further promote a smooth transition from mixed-flow traffic to full autonomy.

The remainder of this paper is organized as follows. Section II introduces the experimental design. Section III presents the behavioral variables and methods for CF model calibration, analyzing behavior evolution and eye-tracking data. Section IV presents and analyzes the results. Section V provides some concluding comments and future directions.

II. EXPERIMENTAL DESIGN AND PARTICIPANT CHARACTERISTICS

This section describes the simulator environment and data collection, articulates the experimental design, and summarizes the participants' basic demographics.

A. Simulator Environment and Data Collection

This study uses a high-fidelity full-cab driving simulator (RDS-2000 by Realtime Technologies shown in Fig. 1(a)) at the Georgia Institute of Technology to conduct the CF experiments. It features a full-size vehicle cabin with 6 degrees of freedom motion base (upward/downward, left/right, forward/backward, pitch, roll, and yaw), and 360-degree surrounded audio and driving view that simulates a real-world driving experience.

The data collected includes: (i) position, speed, and acceleration of all vehicles in the simulated environment (Fig. 1(b)); (ii) biosensor data such as gaze points (from non-intrusive Smart Eye eye-tracking system), heart rate (from Shimmer electrocardiogram unit), and brain electric activity (from OpenBCI electroencephalogram headset); (iii) basic demographics (gender, age, annual mileage, annual income, highest degree earned); (iv) trust level in autonomous driving, ranging from 1 (zero trust) to 5 (strong trust); (v) self-reported aggressiveness (cautious, normal, aggressive); (vi) rank of subjective preference in three CAV control settings (reporting the most, the second, and the least favorable); and (vii) rank of estimated focus level under the three CAV control settings.

B. Design of Independent Variables

Three types of CAV control settings (i.e., SS, SU, and HDV-like) are considered. The control setting of the predecessor CAV is manipulated as a within-subject factor; therefore, each participant will experience all three CAV control settings. The SS CAV is included as it is needed to benefit traffic flow. The SU CAV is included to reflect current level-2 autonomous driving. The HDV-like CAV is included as a human-like baseline to compare to SS and SU CAVs.

The CF behavior of SS/SU CAV is simulated using the discrete-time CTH-RV-RA model as follows [4].

$$\begin{aligned} a_k^{ego} = & k_s(p_k^{pred} - p_{k-1}^{ego} - hv_{k-1}^{ego}) \\ & + k_v(v_{k-1}^{pred} - v_{k-1}^{ego}) \\ & + k_a(a_{k-1}^{pred} - a_{k-1}^{ego}) \end{aligned} \quad (1)$$

where p_k^{ego} , v_k^{ego} , a_k^{ego} are the position, speed, and acceleration

of the ego CAV at time step k , respectively. p_k^{pred} , v_k^{pred} , a_k^{pred} are the position, speed, and acceleration of the immediate predecessor CAV at time step k , respectively. h is the desired time headway of the ego CAV. k_s , k_v and k_a are the control gains for correcting spacing error, speed tracking error, and acceleration tracking error, respectively; their values are tuned based on the frequency domain string stability criterion [26] to achieve SS/SU CF behavior. Specifically, we set $k_s = 0.2s^{-2}$, $k_v = 0.2s^{-1}$, $k_a = 0.4$, $h = 1.75s$ for SS CAV; $k_s = 0.3s^{-2}$, $k_v = 0.1s^{-1}$, $k_a = 0.1$, $h = 1.25s$ for SU CAV. The parameters of SS and SU CAVs are empirically tuned to display noticeable SS and SU behavior and to avoid collision and choppy vehicle motion in the driving simulator environment. The CF behavior of HDV-like CAV is simulated using the IDM with default parameters [23]. The step length is 1/60 seconds.

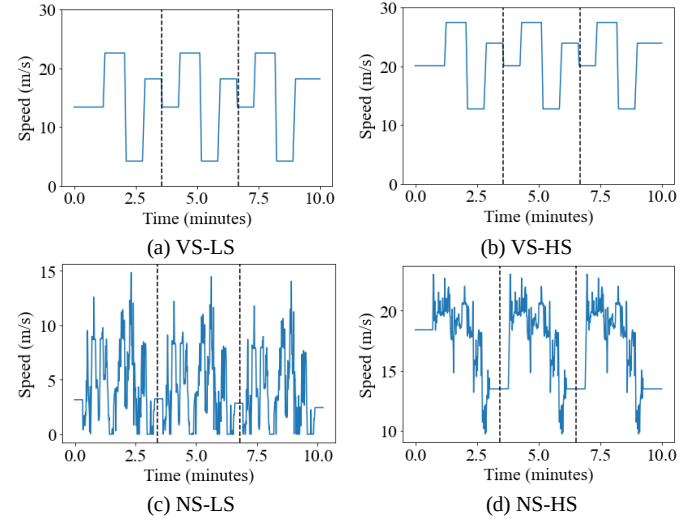


Fig. 2. Lead vehicle trajectory

Generally, the SS CAV can dampen the speed fluctuations from downstream traffic to mitigate traffic congestion, while maintaining larger spacing between vehicles. By contrast, the SU CAV will amplify the speed fluctuations from downstream traffic, while maintaining smaller spacing between vehicles. Note that this is a common feature of the SS/SU control setting, indicating the trade-off between traffic efficiency and string stability. Besides the controller parameter setting, the SU CF behavior can also be triggered by a weak vehicle actuator and faulty state information of the predecessor vehicle. The HDV-like CAV exhibits human-like CF behavior, which displays: (i) speed-dependent string stability performance (e.g., being less SU at low speed than at high speed), (ii) larger desired time headway compared to SS and SU CAVs, (iii) smaller desired acceleration/deceleration when reaching to high speed; and (iv) slow-varying acceleration/deceleration pattern for comfort.

Four types of lead vehicle trajectories are considered: varying-setpoint-low/high-speed (VS-LS/HS), and naturalistic-speed-low/high-speed (NS-LS/HS). The lead vehicle trajectory is manipulated as a between-subjects factor. Therefore, the CF experiment has four groups of participants corresponding to the four types of lead vehicle trajectories.

The VS trajectory means that the lead vehicle conducts a sudden acceleration/deceleration and then maintains a steady speed level for a period (i.e., impulse-type perturbation). The impulse-type perturbation is used to mimic traffic oscillations

in congested and near-congested traffic, which aims to stimulate important CF characteristics related to the capability of dampening speed fluctuations from HDVs. The impulse-type perturbation can be induced by variable speed limit, emergency brakes due to accidents and lane closures, and other traffic control strategies (e.g., variable speed release for connected and autonomous vehicles to suddenly accelerate to improve bottleneck capacity [27]). Remarkably, it is frequently applied to study CF behavior of adaptive cruise control and human drivers [28], [29]. As shown in Figs. 2(a) and (b), the lead vehicle displays trapezoidal speed profiles. The VS-LS case (Fig. 2(a)) has an average speed of around 13 m/s, resembling the transition between mild and heavy congestion. The VS-HS case (Fig. 2(b)) has an average speed of over 22 m/s, representing the transition between free-flow traffic and mild congestion. By contrast, the NS trajectories are constructed using trajectories from the NGSIM dataset [18], containing consecutive acceleration/deceleration movements (i.e., wave-type perturbation in traffic congestion). As shown in Fig. 2(c), in the NS-LS case, the lead vehicle displays consecutive wave-type stop-and-go movements. The average speed is less than 5 m/s, representing the transition between mild and heavy congestion. Fig 2(d) shows the NS-HS case with an average speed of over 18 m/s, where the lead vehicle exhibits consecutive acceleration/deceleration to simulate free-flow traffic and mild congestion. The time length of each trajectory is around 10 minutes. Note that each lead vehicle trajectory contains three cycles of speed pattern (separated by vertical dashed lines in Fig. 2), which will be used to evaluate the behavior evolution of HDV CF behavior.

Remark 1: The design of the lead trajectories factors the perturbation types and speed levels to resemble real-world traffic congestion. The persistent excitation condition in system identification theory [30] is also considered to produce reliable parameter estimates for CF models in section III.

C. Procedure

Before arriving at the lab, each participant was asked to complete a web-based pre-experiment survey to answer questions related to: (i) participation eligibility (e.g., driver license, normal or corrected vision); (ii) basic demographics; and (iii) trust in autonomous driving. After arriving at the lab, participants completed a consent form (regarding using trajectory and biosensor data for research) and a motion sickness protocol (including a practice run and a before-after survey [31]). This 5-min practice run was aimed at familiarizing the participant with operating the driving simulator and mixed-flow traffic. If the participant did not experience motion sickness in the practice run or indicate motion-sickness concerns in the survey, the experiment was continued. Each participant was assigned a prespecified lead vehicle trajectory scenario, and experienced three different predecessor CAV control settings in 3 CF runs. They were given a 3-minute break between runs. The order of CAV control settings was systematically varied in the 3 runs using a Latin Square Design to avoid order effects. Last, in the post-experiment interview administered after the 3 CF runs, participants ranked: (i) their preference for 3 CAV control settings based on CF experience; and (ii) their estimated focus level under 3 CAV control settings. The experiment took around one hour in total.

D. Participant Characteristics

The study includes 80 participants. Eight of them are omitted due to motion sickness and technical difficulties during the experiments. The valid 72 participants include 36 females and 36 males. Their age distribution has a mean of 32.9 years and a standard deviation of 13.01 years: 24 participants are 18-24 years old, 22 participants are 25-34 years old, 11 participants are 35-49 years old, and 15 participants are 50 and over. All participants hold valid US driver licenses, and 88% of them hold their driver licenses for at least 4 years.

III. METHODOLOGY

This section introduces the behavioral variables, the methods to calibrate the CF model and capture the CF behavior evolution, and the visual measure for distracted driving.

A. Behavioral Variables

The string stability norm indicates the propagation of speed tracking error, which is calculated as follows [26]:

$$\gamma = \|v_{1:T}^{ego} - v_{1:T}^{pred}\|_2 / \|v_{1:T}^{pred} - v_{1:T}^{sec.pred}\|_2 \quad (2)$$

where $\|\Theta_{1:T}\|_2 = \sqrt{\Theta_1^2 + \dots + \Theta_T^2}$ is the l_2 norm of the time series $\Theta_{1:T}$. T is the number of time steps of a vehicle trajectory, and $v_{1:T}^{sec.pred}$ is the speed of the second predecessor CAV of ego HDV. A larger γ indicates poorer string stability performance from a driver (i.e., enlarged speed tracking error and speed fluctuations).

The overshoot (OS)/undershoot (US) percentage describes how much the maximum speed increment/decrement of the ego HDV exceeds that of the predecessor CAV:

$$OS = [(A_o - A_c)/A_c] \cdot 100\% \quad (3a)$$

$$US = [(A_u - A_d)/A_d] \cdot 100\% \quad (3b)$$

where A_o (A_c) is the maximum level of speed increment from the ego HDV (predecessor CAV), A_u (A_d) is the maximum level of speed decrement from the ego HDV (predecessor CAV). A larger OS/US percentage indicates more exaggerated overreaction from HDVs and poorer string stability performance under VS type trajectories.

Further, spacing and TTC are used to describe traffic efficiency and safety performance of the ego HDV, respectively. A smaller spacing indicates improved traffic efficiency as more vehicles can operate on roads. A larger TTC indicates improved safety performance as a larger time margin is reserved for drivers to react before collisions.

B. Car-following Dynamical System

To calibrate the CF model, a CF dynamical system is formulated for the ego HDV in (4). It consists of two parts: (i) transition equation describing variations in vehicle states and parameters during the CF process, and (ii) observation equation which records sensor measurements (e.g., ego HDV speed).

$$\begin{aligned} \tilde{x}_k &= [p_k^{ego}, v_k^{ego}, \theta_k]^T = F(\tilde{x}_{k-1}, u_{k-1}) + w_{k-1} \\ &= \begin{bmatrix} p_{k-1}^{ego} + v_{k-1}^{ego} dt + 0.5a_k^{ego} dt^2 + w_{k-1,1} \\ v_{k-1}^{ego} + a_k^{ego} dt + w_{k-1,2} \\ I_{n_\theta} \theta_{k-1} + w_{k-1,3} \end{bmatrix} \end{aligned} \quad (4a)$$

$$y_k = g(x_k, u_k, \theta_k) = v_k^{ego} + n_k \quad (4b)$$

where $\theta_k = [k_s, k_v, h]^T$ is the CF parameter vector of the ego HDV. $u_k = [p_k^{pred}, v_k^{pred}]^T$ and $x_k = [p_k^{ego}, v_k^{ego}]^T$ are the

state vector of predecessor CAV and ego HDV, respectively. $w_{k-1,1}$ and $w_{k-1,2}$ are the zero-mean normally-distributed uncertainties in position and speed dynamics, respectively. $w_{k-1,3}$ is the zero-mean normally-distributed process noise in the evolution of CF parameters. n_k is the zero-mean normally-distributed measurement noise. $a_k^{ego} = k_s(p_{k-1}^{pred} - p_{k-1}^{ego} - hv_{k-1}^{ego}) + k_v(v_{k-1}^{pred} - v_{k-1}^{ego})$ describes the acceleration variations of the ego HDV based on the CTH-RV model. For parameter estimation, as all vehicle states are known, we only need to focus on the evolution of parameters θ_k (i.e., third row of (4a)). The damping ratio is computed as:

$$\zeta = (k_v h + k_s) / 2\sqrt{k_s} \quad (5)$$

The damping ratio reflects the capability to dampen speed fluctuations; $\zeta \geq 1$ indicates that the driver can fully dampen speed fluctuations (SS CF behavior), while $\zeta < 1$ indicates that the driver will amplify speed fluctuations (SU CF behavior).

C. Particle Filter-based Car-following Model Calibration

A PF is used to estimate the distribution of CF parameters (i.e., mean and standard deviation) [24], which aims to produce values similar to sensor measurements y_k . In the formulation, each particle i at time step k represents a set of estimated CF parameters: $\hat{\theta}_k^i = [\hat{h}^i(k), \hat{k}_s^i(k), \hat{k}_v^i(k)]$ with a certain weight (normalized probability). The weight of $\hat{\theta}_k^i$ also indicates the likelihood of a driver's car-following behavior given the stimulus from the predecessor vehicle trajectory. As a Bayesian method, the first key step of PF is to calculate the a priori probability of the particle based on the state transition in (4a):

$$\mathbf{P}(\hat{\theta}_k | y_{1:k-1}) = \int \mathbf{P}(\hat{\theta}_k | \hat{\theta}_{k-1}) \mathbf{P}(\hat{\theta}_{k-1} | y_{1:k-1}) d\hat{\theta}_{k-1} \quad (6)$$

where $\mathbf{P}(\blacksquare)$ is the probability of variable $\blacksquare$. Next, based on the time series of sensor measurement $y_{1:k}$, the a posteriori probability estimation of the particle is computed:

$$\mathbf{P}(\hat{\theta}_k | y_{1:k}) = \frac{\mathbf{P}(y_k | \hat{\theta}_k) \mathbf{P}(\hat{\theta}_k | y_{1:k-1})}{\sum_j \mathbf{P}(y_k | \hat{\theta}_{k,j}) \mathbf{P}(\hat{\theta}_{k,j} | y_{1:k-1})} \quad (7)$$

Algorithm 1 shows the PF iterations. Given the trajectories of ego HDV and predecessor CAV for T time steps, the iterations start with the initial values of N_p particles, where each particle i shares an equal weight $\omega_0^i = 1/N_p$. In line 4, the state propagation is performed based on state transition (4a), which updates the estimated parameter $\hat{\theta}_{k,i}^-$ at step k . In line 5, the a priori distribution of the estimated parameter is computed. Then, the weight of each particle m_i is computed based on the likelihood of producing observation (4b), which is used to compute the a posteriori distribution of estimated parameters in line 5. Finally, we resample the particles based on weight m_i to obtain the updated particles (estimated parameters $\hat{\theta}_{k,i}^+$ to be used in the next iteration) and remove particles with low probabilities (low-accuracy parameters) to improve estimation accuracy. In the implementation, we set $N_p = 200$.

Algorithm 1: Particle filter for CF model calibration

- 1: **Input:** $x_{1:T}$, $u_{1:T}$ N_p , distributions of n_k and w_k
- 2: **Initialize** N_p particles $\hat{\theta}_{0,1:N_p}^+$ from an initial distribution $\mathbf{P}(\theta_0)$. Assign equal weight $\omega_0^i = 1/N_p$ to each particle.

- 3: **for** $k = 1:T$ **do**
 - 4: Obtain $\hat{\theta}_{k,i}^-$ based on (4a)
 - 5: Compute the *a priori* distribution:
 $\mathbf{P}(\hat{\theta}_k | y_{1:k-1}) = \sum_{i=1}^{N_p} \frac{1}{N_p} \delta(\hat{\theta}_k - \hat{\theta}_{k,i}^-)$
 - 6: Compute the *a posteriori* distribution:
 $\mathbf{P}(\hat{\theta}_k | y_{1:k}) = \sum_{i=1}^{N_p} m_i \delta(\hat{\theta}_k - \hat{\theta}_{k,i}^-)$
 - 7: Resample particles: generate u_i from a uniform distribution on $[0,1]$, for all i
If $\sum_{l=1}^{j-1} m_l < u_i \leq \sum_{l=1}^j m_l$, $\hat{\theta}_{k,i}^+ = \hat{\theta}_{k,j}^-$
 - 8: **end for**
-

Note that $\delta(\theta) = \begin{cases} 1, & \theta = 0 \\ 0, & \text{otherwise} \end{cases}$ is the Dirac delta function, and $m_i = \mathbf{P}(y_k - h(\hat{\theta}_{k,i}^-, n_{k,i})) / \sum_{j=1}^{N_p} \mathbf{P}(y_k - h(\hat{\theta}_{k,j}^-, n_{k,j}))$ is the updated weight of particle i . The CF model calibration reflect the CF behavior triggered by different stimuli. However, it cannot explicitly show the detailed evolution of CF behavior. Next, we introduce online parameter estimation method to track the changes in CF parameters throughout the CF tasks.

D. Extended Kalman Filter for Online Parameter Estimation

The EKF is applied to enable the online parameter estimation using speed measurement at each time step. EKF seeks to minimize the estimation uncertainty at each time step to provide time-varying curves of estimated parameters [25], which can be used to interpret the variations in HDV CF behavior (i.e., learning curves) in the CF process. Note that PF is not applied for online parameter estimation here because of the inevitable particle depletion issue (i.e., insufficient number of particles to produce accurate estimation), which requires adding new particles occasionally in the parameter estimation process, leading to irregular spikes in estimated parameters and introducing perturbations in analyzing behavior evolution.

To execute the EKF, we define W and R as the covariance matrices of $w_{k,3}$ and n_k , respectively. Algorithm 2 illustrates the EKF for parameter estimation. After specifying the initial values of CF parameter $\hat{\theta}_0$ and error covariance matrix P_0 , the EKF is executed for the trajectory data with T time steps. The EKF starts with the prediction step where we assume the predicted parameter $\hat{\theta}_{k(-)}$ will be identical to $\hat{\theta}_{k-1}$ (as shown in line 4 of Algorithm 2). Next, the prediction error covariance matrix of $\hat{\theta}_{k(-)}$ is computed in line 5, where $\phi_{k-1} = \frac{\partial F(x_{k-1}, u_{k-1}, \theta_{k-1})}{\partial \theta_{k-1}}|_{\theta_{k-1}=\hat{\theta}_{k-1}} = I_3$ is a 3×3 identity matrix describing how $\hat{\theta}_{k(-)}$ is influenced by estimated parameters in the previous time step, $J_w = \frac{\partial F(x_{k-1}, u_{k-1}, \theta_{k-1})}{\partial w_{k-1}}|_{\theta_{k-1}=\hat{\theta}_{k(-)}} = \mathbb{I}_3$ is a one-dimensional unit vector indicating how measurement noise impacts the $\hat{\theta}_{k(-)}$. Then, in line 6, we compute the Kalman gain, where $H_k = \frac{\partial g(x_k, u_k, \theta_k)}{\partial \theta_k}|_{\theta_k=\hat{\theta}_{k(-)}}$ shows how predicted parameter $\hat{\theta}_{k(-)}$ impacts $g(x_k, u_k, \theta_k)$. The Kalman gain is then used to update the estimated parameter $\hat{\theta}_k$ in line 7 where we correct the error between real-time measurement y_k and estimated measurement computed by $g_k(x_k, u_k, \hat{\theta}_{k(-)})$. The last step is to compute the estimation error covariance matrix (in line 8), where $J_n = \frac{\partial g(x_k, u_k, \theta_k)}{\partial n_k}|_{\theta_{k-1}=\hat{\theta}_{k(-)}} = 1$. P_k is then used in the next iteration to improve accuracy.

Algorithm 2: EKF for online parameter estimation

- 1: **Input:** $x_{1:T}, u_{1:T}, W = 0.01\mathbb{I}_3, R = 0.05$
- 2: **Initialize:** $\hat{\theta}_0, P_0 = I_3, k = 0$
- 3: **for** $k = 1:T$ **do**
- 4: Prediction: $\hat{\theta}_{k(-)} = I_3 \hat{\theta}_{k-1}$
- 5: Prediction error covariance matrix: $P_{k(-)} = \phi_{k-1} P_{k-1} \phi_{k-1}^T + J_w W J_w^T$
- 6: Kalman gain: $K_k = P_{k(-)} H_k^T (H_k P_{k(-)} H_k^T + J_n R J_n^T)^{-1}$
- 7: Updated estimation: $\hat{\theta}_k = \hat{\theta}_{k(-)} + K_k (y_k - g_k(x_k, u_k, \hat{\theta}_{k(-)}))$
- 8: Estimation error covariance matrix: $P_k = P_{k(-)} - P_{k(-)} H_k^T (H_k P_{k(-)} H_k^T + J_n R J_n^T)^{-1} H_k P_{k(-)}$
- 9: **end for**

E. Visual Measure of Distracted Driving

The gaze points from the eye-tracking device are used to study the impact of CAV control setting on driver distraction. The kernel density estimation is performed on gaze points to obtain the gaze distribution. Then, we compute the dispersion of collected N_g gaze points as follows.

$$\text{Disp} = \frac{1}{N_g} \sum_{i=1}^{N_g} \sqrt{(g_{i,x} - \xi_x)^2 + (g_{i,y} - \xi_y)^2} \quad (8)$$

where $g_{i,x}$ ($g_{i,y}$) is the x-coordinate (y-coordinate) of gaze point i , and ξ_x (ξ_y) is the x-coordinate (y-coordinate) of the estimated kernel density mean. The dispersion is used as a visual measure of driver distraction. If a driver does not focus on the CF task, they will potentially look away from the predecessor CAV (location of the red dot), randomly gazing at other areas (e.g., roadside objects, other vehicles, infotainment system, cellphone). This will increase the Disp value.

IV. RESULTS AND ANALYSIS

This section first presents the statistical analysis of behavioral variables, providing intuitive explanations of how CAV control settings, traffic congestion levels, and demographics impact HDV CF behavior. Then, results of car-following model calibration, online parameter estimation, gaze distribution, and simulation of mixed-flow traffic are discussed to show the detailed variations in CF behavior (i.e., sensitivity, desired time headway, driving focus) and the impacts of mixed autonomy on highway capacity and congestion mitigation. The statistical significance level is set as 0.05.

A. Statistical Analysis of Behavioral Variables

Fig. 3 shows that different traffic congestion levels and CAV control settings induce different responses from drivers. Specifically, under the wave-type perturbations (i.e., NS-LS and NS-HS), SS CAV induces better string stability performance from drivers than under SU CAV. However, under the impulse-type perturbations (i.e., VS-LS and VS-HS), SU CAV triggers better string stability performance from drivers than SS CAV. The HDV-like CAV always achieves the smallest γ (i.e., induces the most SS response from drivers). Also, when speeds increase from LS to HS (i.e., congestion level is reduced), drivers tend to introduce more speed

fluctuations to traffic flow. The repeated measures ANOVA validates the impacts of the CAV control setting (F-stats 18.642, p-value <0.001) and the traffic congestion level (F-stats 31.551, p-value <0.001) on γ .

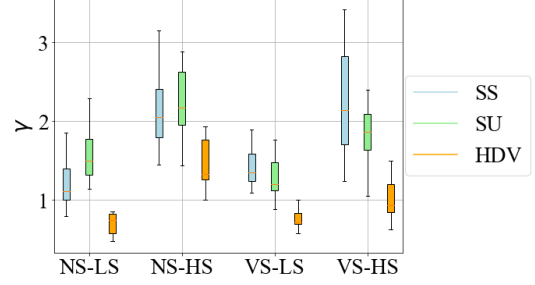
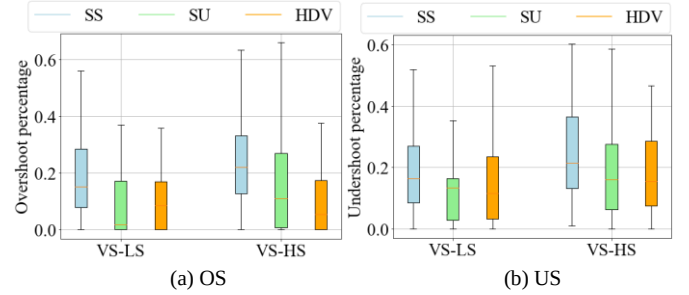
**Fig. 3.** String stability norm**Fig. 4.** Overshoot (OS) and undershoot (US) percentage

Fig. 4 shows SS CAV can induce greater OS/US than SU and HDV-like CAVs under the impact of impulse-type perturbation. This explains the larger γ with SS CAV in VS-LS and VS-HS traffic congestion levels in Fig. 3, indicating that SS CAV can induce more string instability from drivers in VS scenarios. We also observe that higher speeds induce larger OS/US, suggesting that drivers adjust speed more often and overreact to speed perturbations more at higher speeds. The repeated measures ANOVA validates the impacts of CAV control setting (OS: F-stats 9.985, p-value <0.001; US: F-stats 4.709, p-value 0.009) and traffic congestion level (OS: F-stats 8.084, p-value 0.004; US: F-stats 25.711, p-value <0.001).

To explain why SS CAV can deteriorate drivers' string stability performance and explore the underlying mechanism of how CAV control settings influence drivers' string stability performance, mediation analysis [32] is conducted. We hypothesize that the difference in CF behavior between the predecessor CAV and ego HDV will trigger SU response from drivers. Thus, the difference in acceleration/deceleration between the ego HDV and the predecessor CAV is applied as the mediator. Fig. 5 shows the mediation analysis results, where all regression coefficients are significant (p-values are smaller than 0.001). The mediator can reduce the regression coefficient from c to c' . The total impact of CAV control setting (c) is decomposed into a direct impact c' and an indirect impact ab (note that $c = c' + ab$). This indicates that the difference in CF behavior can lead to string instability. The regression coefficient a indicates that SS or SU predecessor CAVs will increase the difference in CF behavior, while HDV-like CAV will reduce it. The b values show that the acceleration/deceleration difference corresponding to SS CAV triggers the most increase in string instability, followed by SU CAV, and then HDV-like CAV. The results illustrate a concern with SS CAV, and suggest that human-like features in CF

behavior can promote more SS CF behavior from drivers.

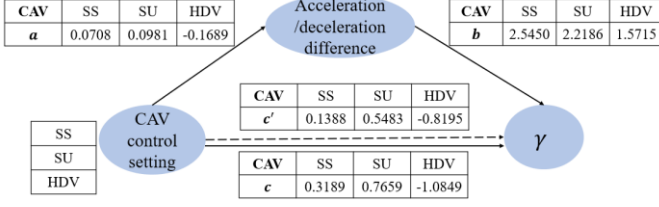


Fig. 5. Results of mediation analysis

Next, we study the impacts on traffic efficiency and safety. Fig. 6(a) shows the spacing between the ego HDV and the predecessor CAV, which indicates that an HDV-like CAV can potentially trigger the largest spacing from drivers, followed by SS CAV, and then SU CAV. However, the spacing difference is not statistically significant (from repeated measures ANOVA: F-stats 1.652, p-value 0.194). More scenarios are needed to examine the impact of CAV control setting on spacings. Fig. 6(a) also shows that drivers maintain larger spacing when driving at higher speed (less congested traffic), as can be expected. This is validated by repeated measures ANOVA (F-stats 75.758, p-value <0.001). Fig. 6(b) presents the TTC of the ego HDV, indicating that SS CAV is associated with the largest TTC, followed by HDV-like CAV and SU CAV. It is also validated by repeated measures ANOVA (F-stats 14.810, p-value <0.001). The TTC also increases with lower congestion (higher speed), which is validated by repeated measures ANOVA: F-stats 3.271, p-value <0.001. The results from γ , spacing, and TTC indicate that traffic congestion can induce potential safety concerns (smaller TTCs and spacings), while improve string stability performance of HDVs. In addition, the CAV control setting inducing more SS and safer HDV behavior can potentially trigger larger spacings (reduced efficiency), indicating trade-offs between string stability and traffic efficiency, and between safety and efficiency.

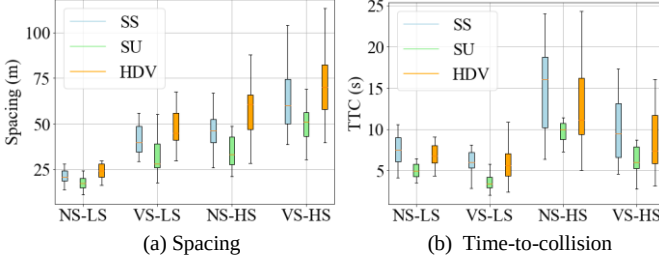


Fig. 6. Spacing and time-to-collision

Next, the repeated measures ANOVA is used to verify the significant impacts of demographic characteristics on γ . Results indicate that the annual mileage (F-stats 2.737, p-value 0.043), age (F-stats 3.054, p-value 0.027), and self-reported aggressiveness (F-stats: 3.321, p-value 0.038) are three significant demographic characteristics that impact the string stability performance of drivers. The next subsection analyzes how these demographic characteristics and traffic congestion levels impact HDV CF behavior using CF model calibration.

B. Car-following Model Calibration

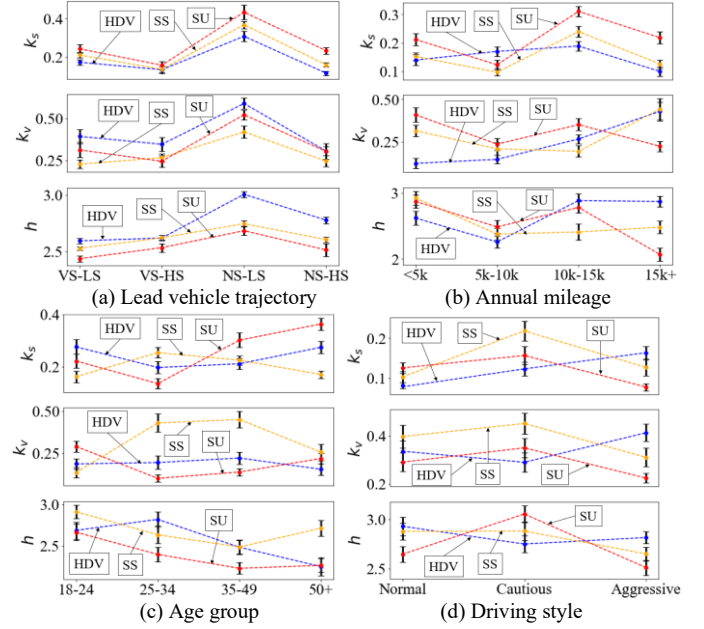


Fig. 7. Estimated CF parameters

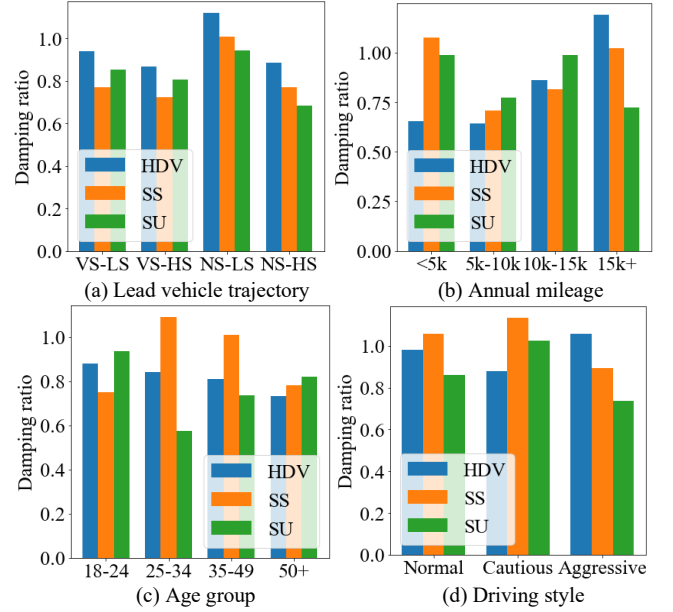


Fig. 8. Estimated damping ratio

Fig. 7(a) shows the estimated CF parameters corresponding to the different traffic congestion levels and CAV control settings, where the thin error bars are the 95% confidence interval (CI) for estimated parameters. The SU CAV induces the largest k_s , followed by SS CAV, and then HDV-like CAV. The HDV-like CAV induces the largest k_v , followed by SU CAV, and then SS CAV. The HDV-like CAV also triggers the largest h , followed by SS CAV, and then SU CAV. As larger k_v can produce more proactive reactions, and large h also introduces more margin to manage the speed fluctuations, the HDV-like CAV induces the greatest damping ratio (computed using (5)), as shown by the blue bars in Fig. 8(a). The large k_s makes drivers react to perturbations in a passive way (becoming spacing-dependent rather than proactively judging the speed difference), which reduces the damping ratio when following the SS CAV (see orange bars in Fig. 8(a)). The small h

triggered by SU CAV forces a driver to follow the predecessor CAV with a smaller spacing, which correspondingly reduces the damping ratio in the CF process (see green bars in Fig. 8(a)). Fig. 8(a) also illustrates that the SS CAV induces the smallest damping ratio under impulse-type perturbation (e.g., VS lead vehicle trajectories). This aligns with our findings in the analysis of γ , presented in section IV.A. Thereby, HDV-like CAVs will ensure the most SS HDV CF behavior, while inducing the largest spacings. SS and SU CAVs will enable less SS HDV CF behavior, while inducing smaller spacings. This indicates a trade-off between traffic efficiency and string stability, implying that properly adjusting CAV control settings are essential to balance string stability and efficiency under different traffic conditions in mixed-flow traffic.

Fig. 7(b) shows the estimated parameters of different annual mileage groups when experiencing different predecessor CAV control settings. It illustrates that when following an HDV-like CAV, drivers tend to be more sensitive to speed variations and maintain larger h as annual mileage increases, which helps to achieve SS CF behavior. However, when following a SS CAV, as annual mileage grows, h gradually converges to around 2.5s, while k_v first decreases and then increases substantially for drivers with annual mileage of over 15k miles. This implies that SS CAV induces weaker dampening of speed fluctuations for drivers with annual mileage between 5k and 15k miles. However, when following a SU CAV, k_s , k_v and h all decrease substantially when annual mileage is over 15k miles, which can trigger more SU CF behavior. Thus, traffic involving SU CAVs and long-mileage drivers will display the most severe shockwave propagation. When the annual mileage is between 5k and 15k miles, the SS/HDV-like CAV induces the smallest sensitivity and h , which leads to reduced damping ratio. This shows that drivers who travel 5k to 10k miles annually are likely to experience no benefits from SS or HDV-like CAV (as shown in Fig. 8(b)). Fig. 8(b) also indicates that SS CAV can help low annual mileage drivers (<5k) to achieve SS CF behavior, while SS and HDV-like CAVs can help drivers with annual mileage of over 15k miles to achieve SS CF behavior. Thereby, the smoothness of traffic flow can be improved by having long-mileage drivers (e.g., commercial truck drivers, Uber drivers) follow HDV-like CAVs, and short-mileage drivers (e.g., students) follow SS CAVs.

Fig. 7(c) shows the estimated parameters for different age groups when experiencing different CAV control settings. As age increases: (i) when following HDV-like CAV, k_s first decreases and then increases, h shows a decreasing trend, and k_v displays minor changes; (ii) when following SU CAV, the trends of k_s and h are similar to those when following HDV-like CAV, while k_v increases and then decreases; and (iii) when following SS CAV, both k_s and k_v first increase and then decrease, while h decreases until the '50+' age group. Thus, driver age primarily impacts sensitivity to spacing changes and desired time headway when following HDV-like/SU CAV. For ages 35 and above, HDV-like CAV induces drivers to be more sensitive to spacing variations, and reduces desired time headway. This leads to a reduced capability to dampen speed fluctuations. The SS CAV can potentially trigger more sensitivity to speed variations, which improves the proactive response to reduce speed fluctuations (larger damping ratios).

Fig. 8(c) also indicates that SS CAV can assist drivers between the ages of 25-49 years to achieve SS CF behavior. Thus, drivers in 50+ and 18-24 age groups obtain minor benefits from SS/HDV-like CAVs. Other control strategies should be developed to improve the smoothness of these drivers.

Fig. 7(d) illustrates that drivers who consider themselves as cautious tend to be the most sensitive to speed and spacing variations (largest k_s and k_v), while drivers who consider themselves as aggressive tend to maintain the smallest h . For drivers who consider themselves as normal drivers, the SU CAV triggers the smallest k_v and h , and the largest k_s , which triggers the worst damping performance (illustrated by the smallest damping ratio in Fig. 8(d)). For cautious drivers, the HDV-like CAV induces the smallest k_v and h , and further leads to the smallest damping ratio in Fig. 8(d). For aggressive drivers, the SU CAV induces the lowest sensitivity and the smallest h , which contributes the most to SU CF behavior. Fig. 8(d) also shows that SS CAV can help normal and cautious drivers achieve SS CF behavior, while HDV-like CAV can promote SS CF behavior for aggressive drivers. Thereby, identifying the aggressiveness of a HDV (using online classification algorithms) and switching to a proper CAV control setting can improve traffic smoothness.

C. Car-following Behavior Evolution

Fig. 9 shows the results of online parameter estimation, where the solid blue curves are the mean values of estimated parameters, the red shaded areas are the 95% CIs of the estimated parameters, and the green vertical dashed lines mark the end time of each cycle. Comparing the three cycles, we notice that as the CF task continues, the HDV-like CAV triggers the least changes in k_v and h , while increasing k_s . The SS CAV triggers the least changes in k_s , while inducing an increasing h and the largest decay rate in k_v . The SU CAV triggers gradual reductions in k_s and h while increasing k_v . The results indicate the different characteristics of time-varying CF behavior in response to different CAV control settings. Compared to the HDV-like CAV, the SS CAV makes drivers less vigilant to speed changes and gradually increases the desired time headway to maintain more comfortable driving experiences. The decreasing k_v and large k_s explain why SS CAVs induce less damping from HDVs. By contrast, the SU CAV makes drivers more sensitive to speed and spacing variations, and gradually reduces h to keep the same pace as the predecessor CAV. The decreasing h and increasing k_s reduce the damping ratio of HDVs when following SU CAVs. Next, curve fitting is performed for the estimated damping ratios using 7th order polynomials. Fig. 10 shows that damping ratios decrease with time. Moreover, with more CF experience, the HDV-like CAV triggers the largest damping ratio from drivers, followed by SU CAV, and then SS CAV. This confirms the results of the SS norm: HDV-like CAV helps drivers achieve the greatest capability in damping speed fluctuations, followed by SU CAV, and then SS CAV. Thus, while SU CAV is not desirable for traffic flow, it can induce drivers to dampen speed fluctuations (in contrast to SS CAV). The results suggest that preventing k_v from waning off with CF experience is an effective solution to alleviate string instability of drivers. This can potentially be achieved through CF speed advisory systems and speed-dependent brake light designs (e.g., a few different brake light

patterns for different speeds and decelerations).

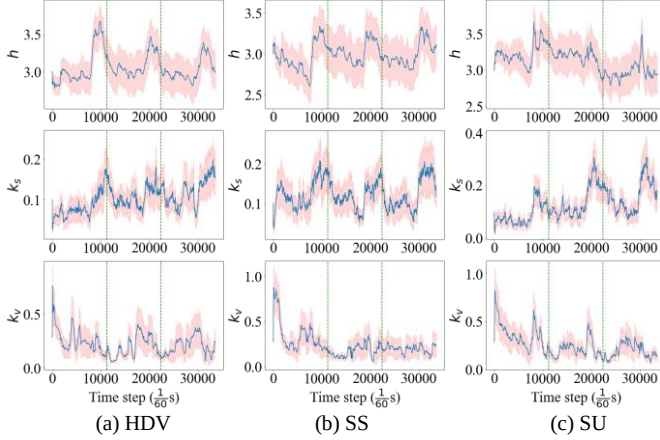


Fig. 9. Results of online parameter estimation. The RMSEs of (a), (b), and (c) are 0.072, 0.068, and 0.081, respectively

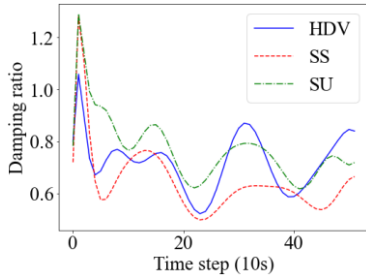


Fig. 10. Evolution of damping ratio

D. Distracted Driving and Driving Preference

Fig. 11 shows the results of estimated gaze distribution. The red area indicates the location of dense gaze points (estimated kernel mean), while the light-yellow areas indicate sparse gaze points (areas that are not frequently checked by drivers).

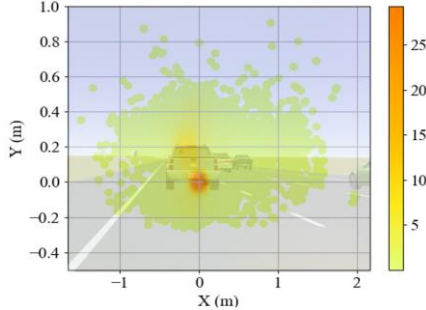


Fig. 11. Gaze distribution

Table I lists the Disp value for each CAV control setting, indicating that the SS CAV induces the largest dispersion in VS-LS, VS-HS, and NA-HS scenarios, while the HDV-like CAV induces the largest dispersion in the scenario of NA-LS. These results indicate that SS CAV can potentially trigger higher levels of driver distraction in the real world, leading to potential safety concerns. Table I also shows that dispersion is larger in heavier traffic congestion (i.e., lower speeds), which further highlights safety concerns in congested conditions (consistent with TTC in section IV.A).

TABLE I

DISPERSION OF GAZE POINTS				
	VS-LS	VS-HS	NA-LS	NA-HS
SS	0.3352	0.2997	0.2829	0.2896
SU	0.3018	0.2648	0.2794	0.2657

HDV	0.3107	0.2848	0.3118	0.2801
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The post-experiment interview indicates that 52% of participants reported being more focused when following SU CAV, while 25% and 14% of participants were more focused on driving in HDV-like CAV and SS CAV scenarios, respectively (the remaining participants could not differentiate between these scenarios). These results suggest that SS CAV can make drivers less vigilant to the traffic and lose focus during driving. Regarding the most preferable CAV control setting, 43% of participants prefer to follow SS CAV, 30% prefer HDV-like CAV, and 15% prefer SU CAV; the remaining participants were indifferent. Participants who prefer SS CAV reckoned that SS CAV presents them with smooth and evenly paced vehicle movements, with reduced braking and stops. Participants preferring HDV-like CAV consider the corresponding CAV movement as more natural and similar to their own CF behavior. Participants who prefer SU CAV report that this control setting can help them gauge the traffic conditions better and stay focused on driving.

In summary, SS CAV is the preferred control setting for a plurality of participants due to its smooth speed profile. However, smoothness and comfort are likely to reduce focus and make the downstream traffic hard to gauge, which can trigger distracted driving. This distraction can induce abrupt acceleration/deceleration from HDVs, which compromises the string stability (larger γ for SS CAVs). Thus, advanced driver assistance systems are essential to prevent distraction for SS CAV to enhance benefits in mixed-flow traffic.

E. Impacts of Mixed Autonomy on Capacity and Congestion

The capacity of a single lane is compared under different market penetration rates (MPRs) of CAVs with different control settings. The free-flow traffic condition is considered where each vehicle travels at a constant speed of 30.5m/s and no lane change or acceleration/deceleration occurs [33]. The HDVs are simulated using the CTH-RV model with calibrated parameters under specific CAV control settings. Fig. 12(a) shows that the highway capacity increases with higher CAV MPR, indicating the potential of CAV to improve highway capacity. SU CAV leads to the largest capacity in free-flow traffic, followed by SS CAV and HDV-like CAV. Based on the simulated capacity and identical jam density, Fig. 12(b) shows the projected fundamental diagram when CAV MPR is 100%. The results illustrate that though SU (HDV-like) CAV can lead to the largest (smallest) capacity, the corresponding congestion wave speed, i.e., the slope of line AD/CD, is also the largest (smallest). This indicates that SU (HDV-like) CAV will lead to the fastest (slowest) shockwave propagation when traffic density is large, causing the most (least) severe traffic congestion. In summary, Fig. 12 validates the trade-off between traffic efficiency and string stability in CAV operations, indicating that it is necessary to switch to a proper control setting to achieve the desired performance under different traffic conditions.

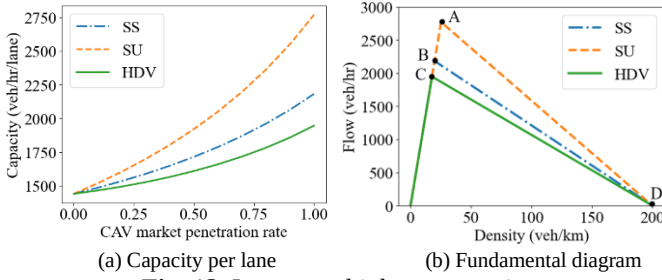


Fig. 12. Impact on highway capacity

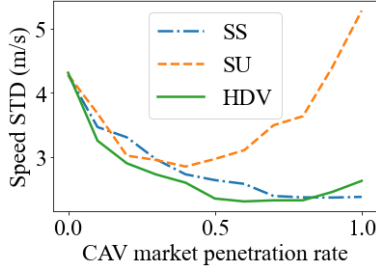


Fig. 13. Standard deviation of vehicle speed

Next, the impacts of mixed autonomy on congestion mitigation are analyzed. Four lead vehicle trajectories (recall Fig. 2) are applied to simulate congested traffic scenarios under different CAV MPRs, and 80 following vehicles follow the lead vehicle and react to shockwaves. Fig. 13 shows the average speed standard deviation (STD) of the 80th vehicle. It can be observed that the speed STD decreases with higher CAV MPR under SS CAV, as SS CAV aims to alleviate traffic oscillations. By contrast, the speed STD under SU CAV first decreases and then increases significantly when CAV MPR is beyond 50%. This is because a SU CAV can trigger SS response from HDVs, which suppresses speed fluctuations under low CAV MPRs. However, if more SU CAVs are included in traffic flow, they will amplify speed fluctuations and propagate shockwaves, leading to large speed STD. Similarly, the speed STD under HDV-like CAV first decreases and then increases, as an HDV-like CAV triggers the most SS response from HDVs while also amplifying traffic oscillations (though not as much as SU CAV). Fig. 13 also illustrates that under low CAV MPR (e.g., less than 40%), HDV-like CAV can achieve the best congestion mitigation performance, followed by SU CAV and SS CAV. Under high CAV MPR, SS CAV outperforms HDV-like CAV, while SU CAV should be avoided as it will induce more severe traffic congestion. Thereby, human-like features should be included in CAV control to ensure the smoothness of mixed-flow traffic when CAV MPR is low. Also, SS CAV should be applied under high CAV MPR to maximize congestion mitigation.

V. CONCLUDING COMMENTS

A. Discussion and Insights

This study conducts driving simulator experiments to investigate HDV CF behavior in mixed-flow traffic. The driving simulator experiments incorporate multiple CAV control settings, traffic congestion levels, and demographics to study HDV CF behavior, which is essential to unveil detailed HDV CF characteristics in the real world. The major findings can be summarized as follows: (i) SS CAV can induce more instability from drivers under impulse-type perturbation due to

the induced acceleration/deceleration difference; (ii) drivers will display different sensitivities when interacting with CAVs in different control settings and under different traffic congestion levels; (iii) drivers' sensitivities to speed (spacing) variations decay (increase) with time; (iv) HDV-like CAV generally triggers the most SS response and the largest spacing from drivers; (v) trade-off exists between safety and string stability performance of drivers; (vi) normal and cautious drivers, drivers 25-49 years old, and drivers with annual mileage lower than 5k miles, can dampen speed fluctuations when following SS CAV; and (vii) SS CAV can lead to driver distraction though it is preferred by a plurality of participants.

Based on these findings, it is necessary to consider drivers' time-varying characteristics and demographics when predicting HDV trajectories. From the dataset perspective, behavior pool involving CAV control setting, traffic congestion level, trip information, demographics, and historical trajectories should be constructed in the digital-twin system [34] [35] to enhance accurate prediction/estimation of HDV CF trajectories. In addition, from the modeling perspective, it is essential to incorporate both model-based and model-free architectures to predict HDV CF behavior. As shown in (9), a CF model-based term $f_{CF}(\tilde{x}_{k-1}, u_{k-1}, \text{tra})$ describing fundamental characteristics of CF behavior (sensitivity to trajectory stimuli and traffic labeled as 'tra'), and a heuristic model-free term $f_{hue}(\text{demo}, \text{trip}, \text{bio})$ incorporating demographics 'demo', trip information 'trip', and biosensor measurements 'bio' can be synthesized using another heuristic function Φ .

$$\tilde{x}_k = \Phi[f_{CF}(\tilde{x}_{k-1}, u_{k-1}, \text{tra}), f_{hue}(\text{demo}, \text{trip}, \text{bio})] \quad (9)$$

In addition, to improve the control performance of a mixed platoon involving HDVs and CAVs, Fig. 14 illustrates a potential optimal platoon formation. Specifically, CAVs in front of an HDV should display more human-like CF behavior or customize it based on the following driver's demographic characteristics. Thereby, while the human-like or customized control setting may sacrifice stability and traffic efficiency, it can effectively prevent HDVs from significantly jeopardizing the control performance achieved by CAVs. Human-like CF behavior can be enabled using: (i) model-based controllers with parameters calibrated using human driving data [36], (ii) optimal control method using expert-designed objective function and constraints to bound control action to stay within human-like range [37] [38], (iii) behavior cloning using deep neural network to imitate human driving data [39], and (iv) reinforcement learning (RL) based on expert-designed reward function [40] or reward function learned from human driving data using inverse RL. Other traffic performance indices can also be incorporated in the methods above to balance the human-like level and the emphasis on traffic performance based on specific HDV behavior and traffic congestion level during CAV operations.

In summary, insights from this study can be applied to develop more realistic CF models to describe HDV behavior in mixed-flow traffic. This further facilitates the comprehension of mixed-flow traffic dynamics, and assists in constructing more realistic mixed-flow traffic simulation environments for training learning-based CAV control strategies. In real-world operations, with more available real-time information (e.g., traffic conditions, demographics, trip information, vehicle

types) in the digital twin architecture, CAVs can adjust control settings based on driver characteristics, and further help HDVs to enhance driving focus and smoothness. This can also promote CAVs to be more acceptable and attractive to consumers, enhancing the scalability of CAVs and the smooth transition from mixed-flow traffic to full autonomy.

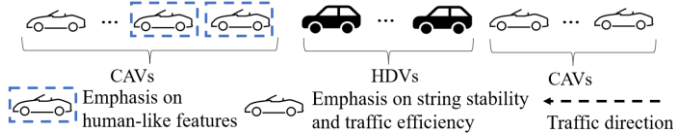


Fig. 14. Optimal mixed platoon formation

B. Future Directions

The study points to some future directions. The first is to factor impacts of drowsiness, road geometry, vehicle type, and trip purpose into the experiments, to further enhance realism. Second, a hybrid-type CF model consisting of model-based and model-free components can be developed to incorporate information on historical trajectories, driver demographics, bio sensor measurements, vehicle types, and trip purpose, to assist tractable trajectory prediction. Third, a heads-up display and augmented reality-based CF assist system can be developed to aid HDVs be more stable when following SS CAVs. Forth, human-like CAV can be developed to balance human-like features and other traffic performance indices.

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