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Calibration of car-following models of human driven vehicles interacting with automated vehicles in mixed traffic: a driving simulator experiment

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ABSTRACT

The deployment of automated vehicles (AVs) on public roads remains limited due to concerns about their interaction with human-driven vehicles (HDVs) in mixed traffic. While previous studies suggest that AVs influence HDV behaviour, the nature of this influence is still not well understood. This study examines how AVs affect HDV car-following behaviour in mixed traffic conditions. Empirical data were collected through a driving simulator experiment in which participants followed a lead vehicle in four scenarios varying in vehicle appearance (AV or HDV) and driving style (AV-like or HDV-like). Car-following behaviour was analysed using the Intelligent Driver Model (IDM) and an extended version (IDM+). The results show that HDVs adapt their behaviour when following AVs, exhibiting smaller jam spacing distances and shorter safe time headways compared to following HDVs. These findings support more accurate assessments of traffic safety and efficiency and contribute to the safe integration of AVs into mixed traffic.

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Automated vehicles; mixed traffic; driving simulator; car-following behaviour; calibration

1. Introduction

In recent years, Automated Vehicles (AVs) have been the focus of the public, the automotive industry, and the scientific community due to their several expected benefits in terms of traffic safety, traffic flow efficiency, accessibility, and environmental impacts (Greenblatt and Shaheen 2015; Piao et al. 2016). Despite this, the pace of their deployment on public roads has been slow and gradual. This is not unexpected as, along with their anticipated benefits, many challenges and uncertainties are associated with their deployment. Among these are the impact of AVs' deployment on traffic safety and efficiency. Crashes involving AVs on public roads (Favarò et al. 2017) have raised concerns and increased skepticism towards what would really be the impact of AVs on public roads, especially when operating alongside, and interacting with, human-driven vehicles (HDVs) and with vulnerable road users (e.g. cyclists, pedestrians). Apart from reported crashes, increasing evidence already shows that interactions between HDVs and AVs are different from interactions among HDVs (Rahmati et al. 2019; Razmi Rad et al. 2021; Reddy, Hoogendoorn, and Farah 2022; Soni et al.

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2022; Zhao et al. 2020). This includes changes such as drivers keeping smaller time headways or showing larger standard deviations in speed when interacting with AVs, which in turn are expected to affect traffic efficiency. Therefore, it is necessary to study these behavioural changes occurring in HDVs when interacting with AVs, to better understand and anticipate the implications on traffic efficiency and safety and take necessary measures and interventions.

A critical part of this investigation involves studying the (microscopic) interactions between AVs and HDVs. Studying these interactions would provide insights into the effects of AVs on the behaviour of HDVs, and vice versa. These interactions could generally be characterised by, for example, car-following behaviour or lane-changing behaviour. Mathematically modelling such interactions is necessary to be able to objectively predict the effects of AV deployment on the traffic performance on public roads (Reddy et al. 2025). Such mathematical models are currently, however, scarce. Apart from a lack of HDV models that consider mixed traffic-specific factors, there is also not yet a clear understanding of the need for models dedicated to mixed traffic conditions.

To address these shortcomings, we focus in this paper on the car-following behaviour of HDVs when following AVs. The reason for selecting car-following behaviour is due to its crucial role and impact on both traffic efficiency and safety. On one hand, car-following behaviour directly affects traffic efficiency aspects such as travel time and delays. And on the other hand, its criticality is also shown by real world crash data. A study reported that the most common type of crash between AVs and HDVs is when the AV is at a standstill while the HDV is moving straight behind the AV, resulting in rear-end collisions (Xu et al. 2019). The reason was said to be the sudden braking of the AV when encountering situations such as a pedestrian crossing the road, which the following HDV driver fails to take timely notice of. Therefore, this research focuses on car-following-behaviour of HDVs when following AVs.

2. Literature review

This section presents first the literature concerning car-following behaviour, followed by a review of studies focusing on the effects of AVs on HDVs' behaviour, and ends with the identified research gaps and research questions.

2.1. Car-following behaviour

Car-following refers to a vehicle's longitudinal driving behaviour, describing how a vehicle follows its leader, including how responsive/sensitive it is to its leader's (changing) state. The scientific literature contains several models to describe car-following behaviour. Several researchers have already conducted extensive review studies and discussions on the various car-following models (Aghabayk, Sarvi, and Young 2015; Brackstone and McDonald 1999; Y. Li and Sun 2012; Saifuzzaman and Zheng 2014). Saifuzzaman and Zheng (2014) broadly classify car-following models as having two perspectives: the engineering perspective and the human factors perspective. Models such as Gipps (Gipps 1981), Intelligent Driver Model (IDM) (Treiber, Hennecke, and Helbing 2000), Optimum Velocity (OV) (Bando et al. 1995), and Nagel-Schreckenberg (Nagel and Schreckenberg 1992) fall under the engineering perspective, and models such as Wiedemann (Wiedemann 1974), visual angle

(Michaels 1963), prospect theory (Kahneman and Tversky 2013) fall under the human factors perspective as in addition to observable external traffic engineering aspects such as distance spacing and speed difference, these models include aspects such as human decision making process or mechanisms of visual perception. Studying and discussing these various existing models is out of scope of this paper.

Most existing car-following models were developed and calibrated for HDVs in conventional traffic (i.e. traffic composed of only HDVs). Such models are also used in microscopic simulation studies to predict mixed traffic performance (S. C. Calvert, Schakel, and van Lint 2017; Guériau and Dusparic 2020; Hu, Huang, and Guo 2020; Jiang et al. 2021; Nishimura et al. 2019; Olia et al. 2018; Talebpour and Mahmassani 2016; Yan, Xiong, and Zhang 2021). These studies rely on the (implicit) assumption that HDVs will drive similarly in mixed traffic as they do in conventional traffic. To our knowledge, only two studies have implemented different/modified car-following models for HDVs in (micro)simulation of mixed traffic (Hua et al. 2020; Li et al. 2023). Hua et al. (2020) studied the impact of different exclusive lane policies in mixed traffic conditions. They modelled HDVs using the Two-state Safe-speed Mode (Tian et al. 2016). Here, they differentiated HDVs following HDVs/AVs by using longer following gaps when following AVs (2.4 s) than when following HDVs (1.8 s). Li et al. (2023) set up a numerical simulation study to model the interactions in mixed traffic and to study the traffic flow characteristics. They had different models for HDVs and AVs when their lead vehicle was an HDV or AV. For HDVs, they used the Gipps's model (Gipps 1981) but modified it such that HDVs would keep an extra distance away (maximum 10 m) when following AVs due to an assumption that HDVs in this case would be more cautious.

In summary, there are several available models used to describe car-following behaviour. However, the focus is on conventional traffic conditions. When it comes to mixed traffic conditions, to the best of our knowledge, only two studies adopted different car-following models, and both did it by explicitly modifying either the following distance or the following time gap when following AVs or HDVs.

2.2. *Impact of AVs on HDVs*

Empirically based studies have investigated the impact of AVs on the car-following behaviour of HDVs in mixed traffic and have found evidence that HDVs modify their car-following behaviour. These studies employed different research methodologies, including driving simulators, field test experiments, and naturalistic driving datasets, as further detailed in the following paragraphs.

Zhao et al. (2020) set up a field test experiment and investigated the car-following behaviour of HDVs when following an AV that differed in its appearance from an HDV. A recognisable AV led AV-believers to maintain smaller time headways, while AV-skeptics maintained larger ones. No differences were found in car-following behaviour when the AV was not recognisable. Mahdinia et al. (2021) analyzed the field test experiment data of Rahmati et al. (2019) where HDVs followed a lead vehicle exhibiting an AV or HDV speed profile (AV not recognisable). They found that HDVs exhibit, on average, 18.8% $\pm$ 6.8% (95% confidence level) lower volatility in speed, and on average, 23.5% $\pm$ 5.3% lower volatility in acceleration when following an AV as compared to following an HDV. Razmi Rad et al. (2021) investigated the car-following behaviour of HDVs when driving next to a dedicated lane for AVs in a driving simulator experiment and compared this to a scenario in which the AVs did not have a dedicated lane but were rather mixed with other traffic. The authors found that the time headway of HDVs driving in the middle lane adjacent to the dedicated AV lane was 0.058 s shorter compared to when they were driving on the rightmost lane, farther from the dedicated AV lane. Aramrattana, Fu, and Selpi (2022) conducted a driving simulator experiment and found that the average car-following headway of HDVs increased from 3 s to 3.5 s when driving among AVs in the main highway scenario but decreased from 2.3 s to 1.3 s when driving among AVs in the on-ramps scenario (the authors indicate that the on-ramp scenario was more congested on the rightmost lane potentially causing HDVs to adopt shorter headways), both compared to driving the same scenario in HDV traffic. AVs were not distinguishable from HDVs and generally had a longer time gap and a lesser lane change propensity than HDVs. de Zwart, Kamphuis, and Cleij (2023) also set up a driving simulator experiment and found that HDVs adopt a shorter median time headway (1.35 s) in 100% AV penetration level condition, compared to when driving in the 50% AV penetration level condition (1.70 s), or the 0% AV penetration level condition (2.09 s). AVs were not visibly recognisable; however, they had shorter time headways compared to HDVs and faster reaction times. Also, they strictly adhered to the speed limit, while HDVs had randomly slightly smaller or larger speeds. There was also a smaller average velocity difference with the lead vehicle in the 100% AV penetration level condition (median −0.23 m/s), compared to the 50% AV penetration level condition (median −0.76 m/s), and the 0% AV penetration level condition (median −1.31 m/s). Wen, Cui, and Jian (2022) analyzed a naturalistic open dataset (Waymo 2019) and found that at lower speeds, HDVs following an AV had larger standard deviations in speed (0.8–1.5 m/s), while at larger speeds, they had smaller standard deviations in speed (0.3–0.5 m/s), when compared to following an HDV. The following time headway of HDVs when following AVs was shorter (2.23 s) than when following other HDVs (2.38 s).

In summary, some studies have looked at the behavioural adaptation of HDVs in mixed traffic and found some evidence for this. These studies adopted different methodologies, ranging from driving simulator studies to naturalistic driving data. In the next section, we present the research gaps that we have identified, and based on that, the research questions.

2.3. Research gaps and research questions

Studies demonstrating evidence that HDVs do adapt their car-following behaviour due to interactions with AVs (e.g. Aramrattana, Fu, and Selpi 2022; de Zwart, Kamphuis, and Cleij 2023; Zhao et al. 2020) are still at a nascent stage. Furthermore, the contributing factors to these impacts are still vastly unexplored. Therefore, there is a need to further investigate the impact of AVs on HDVs' car-following behaviour.

Moreover, most microscopic simulation studies that use car-following models to describe HDVs' longitudinal behaviour in mixed traffic use the same HDV models that are used and calibrated for conventional traffic. This remains an assumption that still needs to be validated considering the observed behavioural adaptation of HDVs. We found only two simulation studies (Hua et al. 2020; Li et al. 2023) that implemented different HDV models depending on whether the leader was an HDV or AV, thus recognising that there is HDV behavioural adaptation. However, they do not provide empirical evidence for the specific changes they make. It also raises the question of how models with modified HDV behaviour differ from those without such modifications. Hence, there is a need for HDV models that consider mixed traffic-specific factors. Or at least, there is a need to investigate whether such modified HDV models are significantly/meaningfully different from the HDV models in conventional traffic. Such new HDV models could be developed either by making some informed assumptions on the parameters of existing models, by calibrating the models using empirical data, or by designing completely new models (Calvert, Wilmink, and Farah 2017).

Based on these identified research gaps, this study addresses the following research questions:

(1) What is the effect of mixed traffic factors on the car-following behaviour of HDVs, as reflected by car-following model parameters?
(2) What is the effect of driver-related factors on the car-following behaviour of HDVs, as reflected by car-following model parameters?

2.4. General approach and outline of the paper

To address the research questions, we first collect empirical data on drivers' car-following behaviour in mixed traffic through a driving simulator experiment. To mathematically capture the observed behaviour, we estimate car-following models that describe driver responses across the different scenarios. Finally, we estimate regression models to gain insight into the specific factors affecting the estimated car-following parameters, which ultimately provide an understanding of the effect of mixed traffic factors on the car-following behaviour of HDVs.

The rest of the paper is structured as follows. Section 3 describes the set-up of the experiment and data collection. Section 4 presents the estimation results of the car-following models. Section 5 follows with the estimated regression models for the parameters. Section 6 discusses all the results, organised by the research questions, and as well the limitations of the study. Finally, Section 7 presents the potential applications and recommendations.

3. Experiment set-up and data collection

3.1. Apparatus and route

A driving simulator experiment was designed to collect data on the car-following behaviour of HDVs in different scenarios. The driving simulator used (Figure 1 left) is located at the Transport & Planning department of Delft University in the Netherlands. It operates using the SCANeR (v1.9) software by AV Simulation. It is a fixed-base driving simulator equipped with a Fanatec steering wheel and pedals, a dashboard mock-up, and three 4 K high-resolution screens, which approximately provide 180° vision.

Drivers followed a route that consisted of three parts. The first part (Part 1) included 3 motorway on-ramps (excluding an initial on-ramp), followed by the second part including 3 provincial road signalised intersections (Part 2), and the third and final part including a straight road section (Part 3). Figure 1 (right) depicts the route. The scope of this study is limited to the final part, the straight road section (single lane, about 5.5 km long), focusing on car-following behaviour. The other prior parts of the route focus on other behaviours,

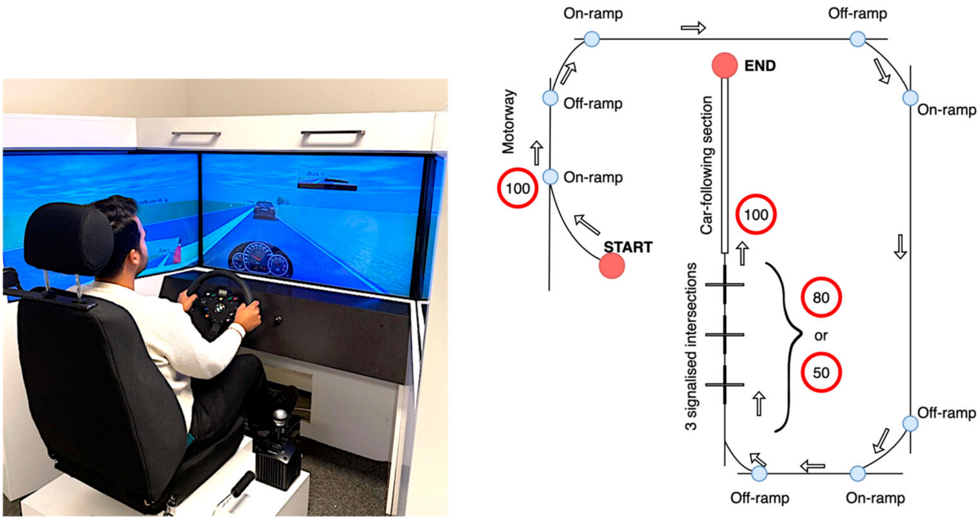

Figure 1. (left) the driving simulator used for data collection showing a driver following an HDV lead vehicle; (right) sketch of the route developed in the driving simulator.

such as merging at on-ramps and driving at intersections on provincial roads, which are out of the scope of this current study. These prior parts allowed the participants to get familiar with the driving conditions, such as the appearance and driving styles of the AVs.

3.2. Protocol and questionnaires

After the approval of the Human Research Ethics Committee of TU Delft, participants were recruited with the support of the Municipality of Delft, with a selection process ensuring age and gender balance. A valid driving license was required to participate in the experiment. Before the driving simulator session, participants filled in questionnaires to collect data on their demographics and driving style (MDSI – which consists of 44 questions that allow for scoring drivers on different driving styles such as Reckless, Anxious, Angry, and Careful) (Taubman-Ben-Ari, Mikulincer, and Gillath 2004). We also measured their trust in technology using a questionnaire (Hagenzieker et al. 2020; Merritt et al. 2013) which had a 5-point Likert-type scale (ranging from strongly agree to strongly disagree) on statements such as '*I usually trust technology until there is a reason not to*' and '*I am likely to trust a technology even when I have little knowledge about it*'. Trust in AVs was measured using another questionnaire, also having the same 5-point Likert-type scale (Payre, Cestac, and Delhomme 2015), with statements such as '*Globally I trust the automated driving system*' and '*I trust the automated system to keep a lane*'. Finally, knowledge of, and experience with different automated driving assistant systems was also measured. For this, the participants were asked to rate their knowledge about and experience using the following systems on a 6-level scale: Cruise Control, Lane Departure Warning, Adaptive Cruise Control, Lane-Keeping Assist, Lane Change Assist, and Forward collision-avoidance.

On arrival at the experiment room, participants were asked to read the information sheet and sign the consent form. Then, the researcher instructed them on the driving simulator equipment and guided them through a familiarisation drive (which generally lasted around

8 min). When the participants felt comfortable, the experiment began, where participants drove 4 different scenarios, with adequate breaks in between. On average, each scenario took about 10 min. After the driving simulator experiment, participants filled in two additional questionnaires to measure their simulation sickness (only 2 participants had to stop earlier due to simulation sickness) and realism in the driving simulator environment. Every participant received compensation of 15 euros as a gesture of gratitude at the end of the experiment.

3.3. Scenarios

When drivers approached the car-following section, they found themselves behind a few slow-moving vehicles (mimicking a traffic jam) and were instructed to follow their lead vehicle (car-following) as they would in real life. The scenario ended after some minutes of car-following (Mean: 5.73 min, SD: 1.42 min). The standard deviation is somewhat large because some drives had to be stopped shortly due to issues with the driving simulator.

Each driver drove four scenarios, excluding an initial familiarisation scenario. The four scenarios varied in terms of the appearance of the vehicle interacting with the human driver and its driving style, as shown in Table 1. The rationale for including the scenario AV HDV is twofold. First, it represents the case where an AV is in manual mode and driven by a human, in which the vehicle retains its AV appearance but exhibits human-like driving behaviour (e.g. Tesla vehicles that can be driven manually when Autopilot or Full Self-Driving (FSD) features are disabled). Second, this case enables us to disentangle the effect of vehicle appearance from that of driving style. Moreover, AVs could, in principle, be programmed to adopt driving patterns similar to human drivers (e.g. shorter headways, higher speeds). The AV was chosen to be white coloured because the white colour for vehicles has a relatively neutral score on aggressiveness scales (Davies and Patel 2005). Participants were informed and shown what the AV would look like before they drove the AV appearance scenarios (Figure 2). If, for some reason, the participant had to stop mid-way (due to an error in following the instructions, or simulator technical issues), then that scenario would be repeated starting from the next Part. For example, if a scenario was stopped in Part 2 (due to technical issues), then the participant would drive the same scenario, but starting from Part 3. We noted this under a variable ‘Trial’. A participant could therefore do multiple ‘trials’ for the same scenario. It is to be noted that multiple trials rarely occurred.

3.4. Vehicle behaviours

Globally, we classified the behaviour of the interacting vehicle as HDV style or AV style. In the route prior to the car-following section, the interacting vehicles drove differently as per the scenario. In general, AV driving style meant strictly following the speed limit and maintaining consistent and constant time headways (decided based on ACC settings found in several commercial car manuals). HDV driving style meant slightly exceeding the speed limit and varying time headways (derived from real-world data on provincial roads provided by the Province of Noord-Holland). When the participant merged onto the motorway from an on-ramp, AVs approaching the on-ramp on the motorway maintained a fixed time gap

Figure 2. The appearance of the AV vehicle in the driving simulator.

Table 1. Scenarios with their AV appearance and driving styles of the interacting vehicle.

Scenario name	AV appearance	AV driving style
HDV HDV	HDV	HDV
HDV AV	HDV	AV
AV AV	AV	AV
AV HDV	AV	HDV

of 2 s, while HDVs had alternating gaps of 1, 2, and 3 s. This is important to note, as even though the scope of this paper is limited to the car-following section, drivers experience the conditions of the scenario (their interactions with AVs or HDVs) earlier in the route, which could affect the way they drive in the car-following section.

The car-following section consisted of a single lane road, and a platoon of four vehicles was preplaced, where the first vehicle was defined to follow a specific speed profile. The other vehicles' desired velocities were set to be larger than the speed limit to ensure that they followed the first vehicle actively. The last vehicle in the platoon became the lead vehicle for the participating driver. This lead vehicle's appearance was as HDV or AV as per the scenario, with no other difference. We designed the speed profile for the first platoon vehicle, aiming at a 'complete trajectory', considering the need for calibrating a car-following model (Sharma, Zheng, and Bhaskar 2018). Figure 3 shows the two speed profiles of the lead vehicle experienced by drivers. While the two lead vehicles' speed profiles share common elements such as driving segments at 70, 50, and 30 km/h, as well as acceleration and deceleration phases, the differences between them lie in the order and combination of these segments. Specifically, each profile presents these elements in a different sequence (e.g. transitions such as 70→50, 50→30, 30→70), alongside variations such as accelerations to 50 or 70 km/h and a harsh braking event to 0 km/h. This design ensures that both profiles contain comparable components while maintaining distinct patterns, thereby avoiding predictability for the following drivers' vehicles.

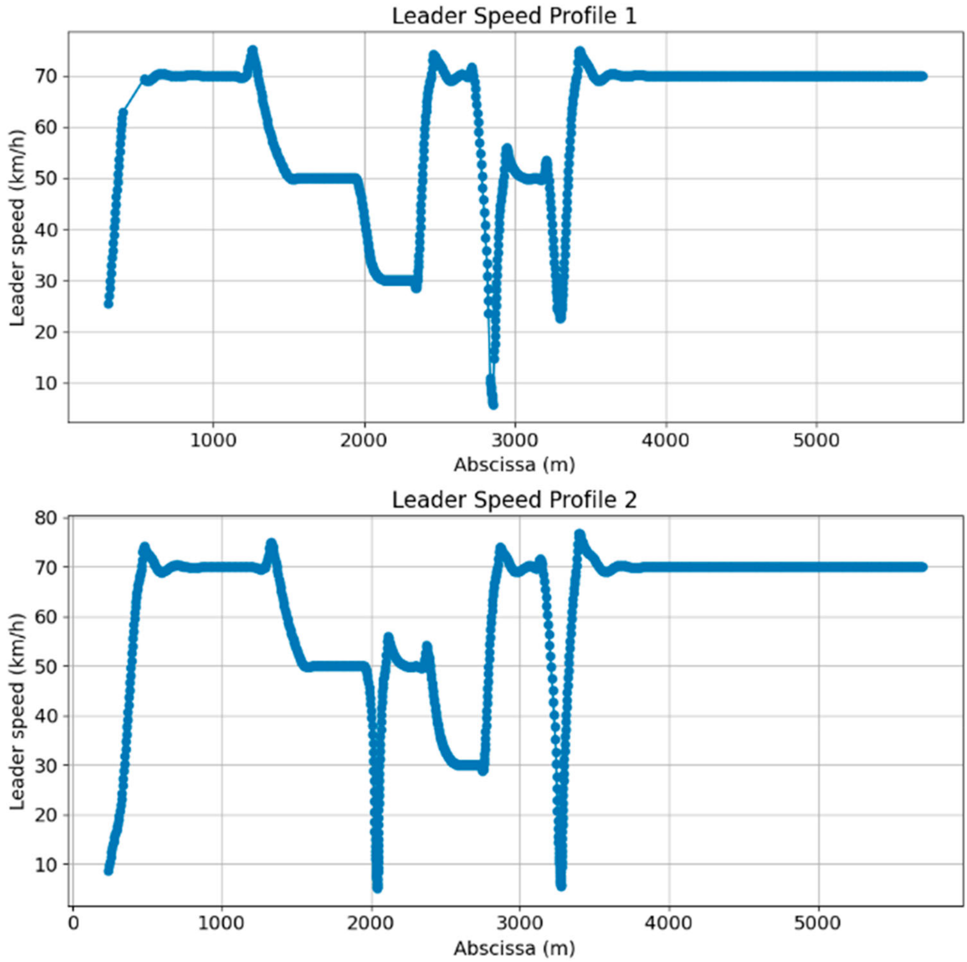

Figure 3. The two speed profiles of the leader vehicle.

3.5. Data collection

It is possible in the driving simulator to export data per scenario. This data consists of over 50 state variables of every vehicle in the scenario. Table 2 presents only the relevant variables for our study and which were extracted. Every variable also includes the vehicle ID and timestamp. We exported the data at a frequency of 4 Hz (4 observations every second), which was sufficient for this type of analysis (Treiber and Kesting 2013). We filtered the dataset for the car-following part of the scenario and for relevant state variables only as detailed in Table 2. Using state variables that describe the vehicle positions and speeds, we calculated the space and time headways of the subject vehicle. Finally, this resulted in a dataset that consisted of all the state variables (those obtained directly from the simulator and the ones we calculated) for all drivers, for all scenarios. We also included the order in which drivers encountered the scenarios in the dataset. The final dataset consisted of 204,164 observations of car-following for 47 participants.

Table 2. Relevant variables exported from the driving simulator.

Variable name	Unit	Variable use
Position	m	The absolute position of the vehicle. Specified in order: x, y, z, heading, pitch, roll.
Speed	m/s	The speed of the vehicle. Specified in this order x, y, z, heading, pitch, roll.
Acceleration	m/s^2	The acceleration of the vehicle. Specified in this order x, y, z, heading, pitch, roll.
Road Id		The ID of the road section where the vehicle is driving.
Road Abscissa	m	The curve distance of the vehicle along the current road.
Lane Id		The ID of the lane of the road where the vehicle is driving.

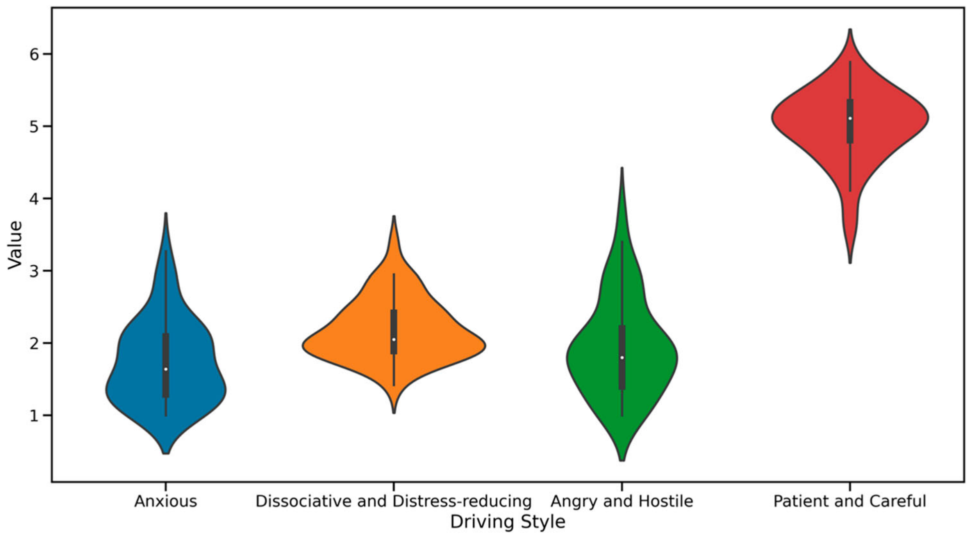

Figure 4. Participants' driving styles distribution (violin plot) calculated from the MDSI driving style evaluation questionnaire.

3.6. Participants

In total, 47 drivers took part in the driving simulator experiment. We categorised them into three balance age categories. There were 16 younger (25–45) drivers (8 male, 8 female), 16 middle-aged (45–65) drivers (8 male, 8 female), and 15 older (70+) drivers (10 male, 5 female). In general, there was a relatively good representation of the different age and gender groups. Figure 4 shows the driving style distribution across all the drivers, calculated from the MDSI driving style evaluation questionnaire. One thing that stands out is that most drivers have a higher extent of stated Patient and Careful driving style.

4. Estimation of the car-following model

To understand the car-following behaviour of drivers in the different scenarios, we decided to estimate a car-following model per scenario. The estimated parameters of the car-following model give insights into the nature of car-following behaviour, while differences in these parameters across scenarios reveal the effect of the investigated factors in this study. In this section, we first select an appropriate car-following model, then describe the estimation process, and finally examine the estimated parameters.

4.1. Model selection

We selected the Intelligent Driver Model (IDM) (Treiber, Hennecke, and Helbing 2000) and its adapted version, the IDM+ (Schakel, Van Arem, and Netten 2010), as the car-following models to be investigated in this study. The IDM is a frequently used model that considers both the desired velocity and the desired space headway of the driver and is known to perform relatively well when compared to observed car-following behaviour (Punzo, Zheng, and Montanino 2021; Saifuzzaman and Zheng 2014). Also, the model is more suitable for estimation since it is smooth (continuously differentiable) and has no explicit delay, which makes it more convenient for some optimisation methods. The IDM+ offers more reasonable capacity values, and with no large acceleration differences from the IDM in most cases (except when the speed is much larger than the desired velocity and the spacing is much smaller than the desired spacing) (Schakel, Van Arem, and Netten 2010). The IDM+ achieves this by applying a minimisation between the free flow term and the interaction term of the IDM. This makes the smooth-topped equilibrium fundamental diagram of the IDM change to a triangular shape. However, due to the minimum operator, the IDM+ is not continuously differentiable, which for our selected optimisation method was not a problem. Equations 1 and 2 describe the IDM and the IDM+ models, respectively, with Equation 3 belonging to both models. Both models are similar in their parameters, differing only in their formulation. While we do not aim to conduct a rigorous analysis into different model types, this comparison remains interesting as it highlights the isolated effects of formulation.

$$\dot{v}_\alpha = a^{(\alpha)}.\left[1-\left(\frac{v_\alpha}{v_0^{(\alpha)}}\right)^\delta-\left(\frac{s^*(v_\alpha,\Delta v_\alpha)}{s_\alpha}\right)^2\right] \tag{1}$$

$$\dot{v}_\alpha = a^{(\alpha)}.min\left[1-\left(\frac{v_\alpha}{v_0^{(\alpha)}}\right)^\delta,1-\left(\frac{s^*(v_\alpha,\Delta v_\alpha)}{s_\alpha}\right)^2\right] \tag{2}$$

$$s^*(v,\Delta v) = s_0^{(\alpha)}+s_1^{(\alpha)}\sqrt{\frac{v}{v_0^{(\alpha)}}}+T^\alpha v+\frac{v\Delta v}{2\sqrt{a^{(\alpha)}b^{(\alpha)}}} \tag{3}$$

Where α is a vehicle, $\dot{v}_\alpha$ is its acceleration, $a^{(\alpha)}$is the maximum acceleration (termed as 'alpha' henceforth), v_α is the velocity, $v_0^{(\alpha)}$ is the desired velocity (termed as v0 henceforth), δ is the acceleration exponent, $s^*(v_\alpha,\Delta v_\alpha)$ is the desired minimum gap, s_α is the actual gap, $s_0^{(\alpha)}$ and $s_1^{(\alpha)}$ are the jam distance (where $s_1^{(\alpha)}$is the speed-dependent part of jam distance, which is set to 0 for simplicity (Treiber, Hennecke, and Helbing 2000)) ($s_{,00}^{(\alpha)}$ termed as s0 henceforth), v is the velocity, T^α is the safe time gap (termed as T henceforth), Δv is the velocity difference, $b^{(\alpha)}$ is the comfortable deceleration (termed as 'beta' henceforth).

4.2. Estimation procedure and outcome

We used the data from the driving simulator to estimate the IDM and IDM+. The process of estimation can be described as follows:

(1) Definition of the IDM and IDM+ models.

(2) Identification of the input variables (speed, headway, etc.) (termed as state variables).
(3) Identification of the output variable – in our case, it is the acceleration of the ego vehicle.
(4) Identification of the parameters to be estimated (v0 desired velocity, T safe time gap, s_0 jam spacing, alpha max acceleration, beta comfortable deceleration), along with their feasibility constraints (for example, the parameter must be non-zero).
(5) Deciding on an initial set of parameters. The initial set of parameters was randomly selected within context-dependent bounds, as per good practice. The initial parameter bounds were:
    $s0$: (minimum_spacing −0.2, 20)
    T: (max(0.5, minimum_time_headway −0.2), 10)
    alpha: (0.5, max_acceleration + 1.5)
    beta: (max_deceleration −0.5, 6.5)
    v0 bounds were manually defined (in m/s): (5, 35)
(6) Using this initial set of parameters, along with the state variables of the vehicle in the current time step as input to the IDM and IDM+ models, the calculation of the acceleration (output variable) is performed.
(7) Using the calculated acceleration, updating the state variables of the vehicle at the next time step (new position, new speed, etc.).
(8) The error between calculated and observed (from the data) state variables is calculated. The selected state variable is termed as the Measure of Performance (MoP) and the error indicator Goodness of Fit (GoF).
(9) Updating the initial parameter values with the intention of minimising the error.
(10) Continue steps 4–7 until satisfactory conditions are met.
(11) Resulting in the final 'best' set of parameter estimates.

This estimation process required some decisions to be made. As a Measure of Performance (MoP), we selected spacing. As a Goodness of Fit (GoF) indicator, we selected Root Mean Squared Error (RMSE). As the optimisation method, we selected the Genetic Algorithm. These decisions were made based on appropriateness and best practices for calibration of car-following models, as identified in Punzo, Zheng, and Montanino (2021). We applied the estimation process on one single trajectory at a time. This results in a different set of parameter estimates for every driver-scenario combination. The estimation process was performed using the Delft Blue supercomputer (Delft High Performance Computing Centre (DHPC) 2024).

The parameters estimation procedure was run on all driver-scenario combinations. In total, car-following parameters for 219 trajectories were estimated. Excluding the familiarisation drive and the trajectories that had extremely large time headway (greater than 10 s) and distance headway (greater than 300 m), resulted in a final set of 173 trajectories with their estimated parameters. Figure 5 shows how these final trajectories were distributed between the 4 scenarios, the 4 orders, and the trials. Overall, there is a good balance between the scenarios and orders, therefore vastly reducing any bias in these variables.

Figure 6 shows the overall boxplot distributions of the parameters over all scenarios for the IDM (a) and the IDM+ (b). The distributions between the two models look similar. Comparing the median values of IDM with that of IDM+ shows that for the IDM+, the safe time

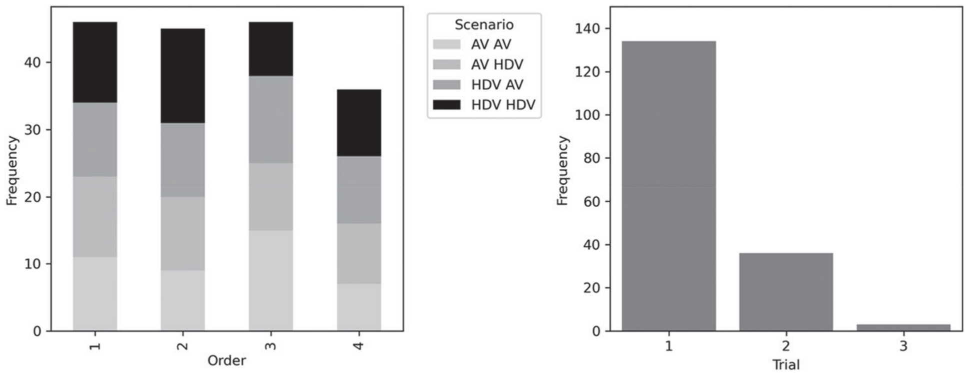

Figure 5. Distribution of final trajectories across scenarios, orders, and trials.

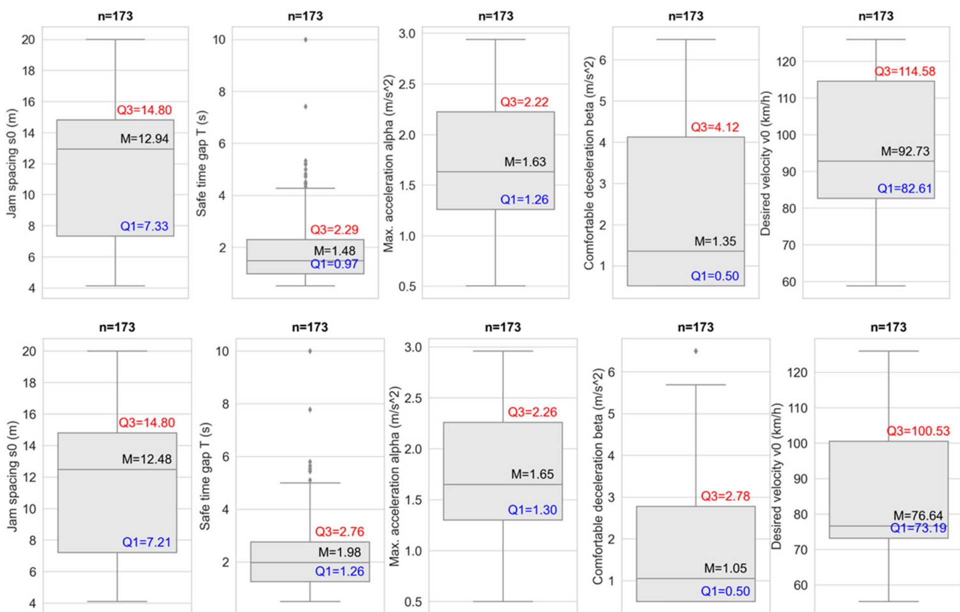

Figure 6. Boxplot distributions of the estimated parameters for the IDM (top) and IDM+ (bottom).

gap (T) is 0.5 s larger, the comfortable deceleration (beta) is 0.3 m/s^2 smaller, the desired velocity (v0) is about 16 km/h smaller, and the jam spacing (s0) and maximum acceleration (alpha) are very similar. Also, the inter-quartile range for comfortable deceleration is larger for the IDM compared to the IDM+.

4.3. Estimated parameters

To help further interpret the results, these parameters were aggregated per scenario. Figures 7 and 8 show box plots of the parameter estimates, per scenario, for the IDM and IDM+, respectively. Certain differences can be observed. For instance, the jam spacing for the scenarios in which the lead vehicle is recognisable as AV, i.e. AV AV (AV Appearance, AV Driving

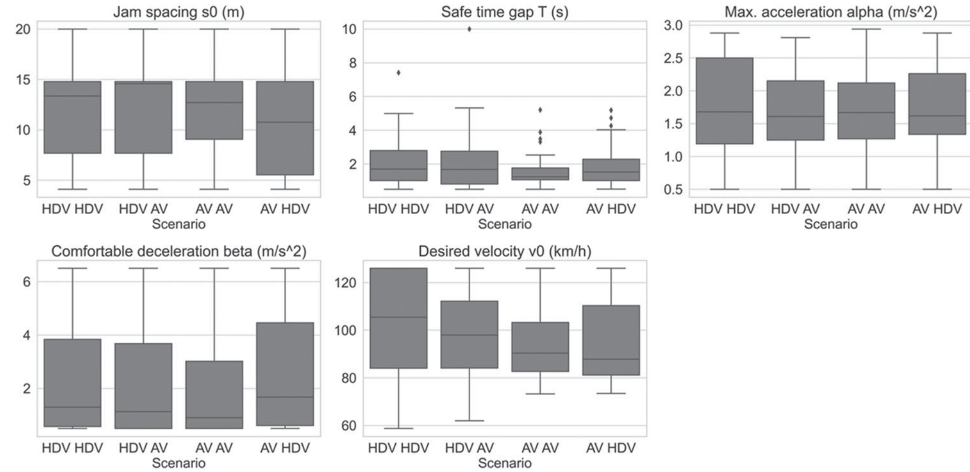

Figure 7. Boxplot distribution of the IDM parameters grouped by Scenario (Appearance – Driving Style).

style) and AV HDV (AV Appearance, HDV Driving style), seem smaller than the other two scenarios in which the lead vehicle is recognisable as HDV. Also, the safe time gap, especially for the AV AV scenario, seems smaller. The median comfortable deceleration for the scenario AV HDV seems larger than the others. The largest visible changes are for the desired velocity, with the conventional traffic scenario HDV HDV having the largest median desired velocity, and the least median desired velocities are for the scenarios AV AV and AV HDV (in both scenarios, the vehicle is recognisable as AV). The changes in desired velocity medians are less noticeable in the IDM+ compared to the IDM.

Tables 3 and 4 present the median and standard deviation of the parameters for the different scenarios, and the differences from the base HDV-HDV scenario for the IDM and IDM+, respectively. What is notable is that the AV AV and AV HDV scenarios have the largest number of green shaded cells, indicating that the largest differences occurred in these scenarios, where the AV was recognisable. This is noticeable for both the IDM and IDM+, but in particular for the IDM+. Additionally, the predominantly white cells in the Values column for AV AV show that, except for median jam spacing, median max acceleration, and SD comfortable deceleration, the AV AV scenario had the smallest values for almost all parameters.

Friedman tests were conducted separately for the IDM and IDM+ model parameters to examine whether there are statistically significant differences in median values across the four driving scenarios. For the IDM model, no significant scenario effects were observed (for minimum gap (s_0), $\chi^2(3) = 5.36$, $p = .147$; headway time (T), $\chi^2(3) = 2.04$, $p = .563$; acceleration (α), $\chi^2(3) = 2.36$, $p = .502$; deceleration (β), $\chi^2(3) = 0.42$, $p = .936$; or desired speed, $\chi^2(3) = 4.63$, $p = .201$ (all $N = 30$)). In contrast, for the IDM+ model, the Friedman test indicated a significant effect of scenario on headway time median (T), $\chi^2(3) = 12.86$, $p = .005$, $N = 30$, Kendall's W $= 0.14$, reflecting a small-to-medium effect size. No significant effects were found for s_0, α, β, or desired speed (all $p > .05$). Post-hoc Wilcoxon signed-rank tests for T did not reveal any pairwise differences that survived Holm–Bonferroni correction (all adjusted $p > .05$). Overall, at this aggregated level of analysis, no robust scenario-dependent differences were observed across the IDM and IDM+

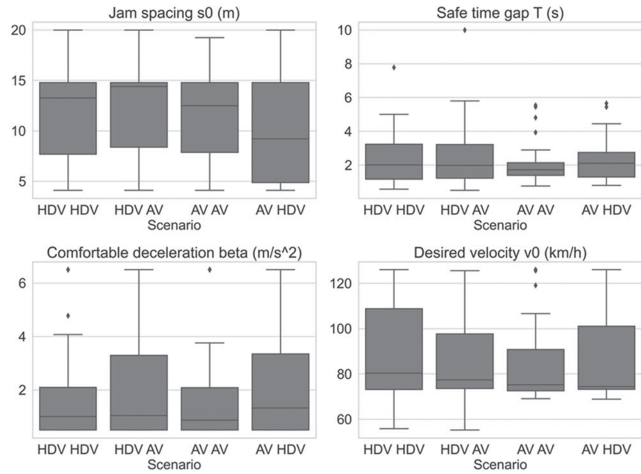

Figure 8. Boxplot distribution of the IDM+ parameters grouped by Scenario (Appearance – Driving Style).

Table 3. Parameter estimates for IDM.

Parameter	Indicator	Values				Difference with HDV HDV		
		HDV HDV	HDV AV	AV AV	AV HDV	HDV AV	AV AV	AV HDV
Jam spacing s0 (m)	Median	13.36	14.58	12.72	10.76	1.23	-0.64	-2.60
	SD	4.80	4.76	4.10	4.49	-0.03	-0.70	-0.31
Safe time gap T (s)	Median	1.70	1.68	1.25	1.52	-0.02	-0.45	-0.18
	SD	1.44	1.78	0.93	1.14	0.35	-0.51	-0.30
Max acceleration alpha (m/s^2)	Median	1.68	1.61	1.67	1.62	-0.07	-0.01	-0.06
	SD	0.71	0.66	0.59	0.63	-0.05	-0.12	-0.08
Comfortable deceleration beta (m/s^2)	Median	1.30	1.13	0.91	1.68	-0.17	-0.40	0.38
	SD	2.23	2.19	2.34	2.38	-0.04	0.11	0.15
Desired velocity v0 (km/h)	Median	105.45	97.96	90.43	87.82	-7.49	-15.02	-17.63
	SD	20.37	18.11	15.63	17.62	-2.26	-4.74	-2.75

Note: Values shaded greyscale (median, SD); 'Difference with HDV HDV' shaded green to white (median, SD).

Table 4. Parameter estimates for IDM+.

Parameter	Indicator	Values				Difference with HDV HDV		
		HDV HDV	HDV AV	AV AV	AV HDV	HDV AV	AV AV	AV HDV
Jam spacing s0 (m)	Median	13.27	14.41	12.50	9.21	1.15	-0.77	-4.06
	SD	4.80	4.50	4.02	5.20	-0.30	-0.78	0.40
Safe time gap T (s)	Median	2.01	1.98	1.72	2.11	-0.03	-0.29	0.10
	SD	1.48	1.88	1.11	1.23	0.40	-0.38	-0.25
Max acceleration alpha (m/s^2)	Median	1.81	1.64	1.67	1.58	-0.17	-0.15	-0.23
	SD	0.68	0.67	0.55	0.63	-0.01	-0.13	-0.06
Comfortable deceleration beta (m/s^2)	Median	1.00	1.04	0.87	1.32	0.04	-0.13	0.32
	SD	1.96	2.30	2.07	2.24	0.34	0.11	0.29
Desired velocity v0 (km/h)	Median	80.38	77.40	75.28	74.45	-2.98	-5.10	-5.94
	SD	21.32	17.44	15.22	19.82	-3.88	-6.10	-1.50

Values shaded greyscale (median, SD); 'Difference with HDV HDV' shaded green to white (median, SD).

Table 5. Comparing estimates and goodness of fit of IDM and IDM+ (Diff relates to the difference in estimates between IDM and IDM+).

Parameter		HDV HDV			HDV AV			AV AV			AV HDV		
		IDM	IDM+	Diff	IDM	IDM+	Diff	IDM	IDM+	Diff	IDM	IDM+	Diff
s0	Median	13.36	13.27	-0.09	14.58	14.41	-0.17	12.72	12.50	-0.22	10.76	9.21	-1.55
	SD	4.80	4.80	0.00	4.76	4.50	-0.26	4.10	4.02	-0.08	4.49	5.20	0.71
T	Median	1.70	2.01	0.32	1.68	1.98	0.30	1.25	1.72	0.48	1.52	2.11	0.59
	SD	1.44	1.48	0.04	1.78	1.88	0.10	0.93	1.11	0.18	1.14	1.23	0.09
alpha	Median	1.68	1.81	0.13	1.61	1.64	0.03	1.67	1.67	0.00	1.62	1.58	-0.04
	SD	0.71	0.68	-0.02	0.66	0.67	0.02	0.59	0.55	-0.04	0.63	0.63	0.00
beta	Median	1.30	1.00	-0.30	1.13	1.04	-0.09	0.91	0.87	-0.04	1.68	1.32	-0.36
	SD	2.23	1.96	-0.28	2.19	2.30	0.11	2.34	2.07	-0.27	2.38	2.24	-0.14
v0	Median	105.45	80.38	-25.07	97.96	77.40	-20.56	90.43	75.28	-15.15	87.82	74.45	-13.38
	SD	20.37	21.32	0.95	18.11	17.44	-0.67	15.63	15.22	-0.41	17.62	19.82	2.20
RMSE	Mean	12.91	12.70	-0.21	16.37	15.99	-0.38	13.83	13.92	0.09	14.02	13.60	-0.42
	SD	9.12	9.08	-0.04	22.48	19.3	-3.18	6.58	6.96	0.38	9.31	7.95	-1.36

parameter median estimates. The Friedman test indicated a significant scenario effect for headway time (T) in the IDM+ model ($\chi^2(3) = 12.86$, $p = .005$). However, actual group-level medians differed only slightly across scenarios, suggesting that the effect reflects subtle within-participant ranking patterns rather than meaningful scenario-dependent differences in headway time.

Fligner-Killeen test was conducted separately for the IDM and IDM+ model parameters to examine the difference in variability across the four driving scenarios. For the IDM, the global tests indicated no significant differences in variance for s0, alpha, beta, or v0 (all $p > .16$). In contrast, the parameter T (time headway) showed significant heterogeneity of variance across scenarios ($\chi^2 = 11.57$, $p = .009$). Post-hoc tests (Holm-Bonferroni corrected) were conducted for a pairwise differences in variances between the scenarios. These revealed that scenarios HDV HDV and HDV AV exhibited significantly greater variability in T compared to scenario AV AV (adjusted $p = .021$ and $p = .010$, respectively), while other pairwise contrasts were non-significant. For the IDM+ model, variability in s0, alpha, and beta did not differ across scenarios (all $p > .21$), but both v0 ($\chi^2 = 8.61$, $p = .035$) and T ($\chi^2 = 9.76$, $p = .021$) did. Pairwise tests showed that scenario HDV HDV had significantly greater variability in desired speed than scenario AV AV ($p = .012$), and that scenarios HDV HDV and HDV AV exhibited significantly greater variability in T compared to scenario 3 ($p = .028$ and $p = .047$, respectively). These results suggest that participants' behaviour was more homogeneous in scenario AV AV, particularly with respect to time headway and desired speed, whereas variability in other parameters remained consistent across conditions.

To get a better insight regarding the differences between the IDM and IDM+, Table 5 presents the estimated parameters of both car-following models across the different scenarios. For each scenario, the third column reports the differences in estimated parameter values between the IDM and IDM+. Additionally, the RMSE, which is the goodness-of-fit indicator, is also reported for all the scenarios for the two models. The columns indicating the differences are shaded from green (greatest positive difference) to red (greatest negative difference). Overall, there are some notable differences. The median desired velocity values have the greatest differences, with the IDM+ having, in general, smaller desired velocities compared to the IDM for all scenarios. Also, the median time headway is greater for the IDM+ compared to the IDM, for all scenarios. As for goodness of fit (RMSE), both models have similar values in general for all scenarios. Given that the actual spacing had a Mean of 56.5 m and SD 41.1 m, the RMSEs are generally around 25% of the mean spacing, which is reasonably good and similar to previous estimations using a genetic algorithm for the IDM (Kesting and Treiber 2008).

5. Regression modelling of parameters

The estimation process resulted in a unique set of parameters for every driver-scenario-trial combination. Our goal is to understand the effect of mixed traffic on the estimated parameters of the IDM and IDM+, and hence on the car-following behaviour. We estimated five univariate linear mixed models with random intercept, one for each estimated car-following parameter (the dependent variables), since all five parameters are continuous variables. These are: s0 (jam spacing), T (safe time gap), alpha (maximum acceleration), beta (comfortable deceleration), and v0 (desired velocity). The independent variables were the scenario-related variables, which included the AV's appearance and AV's driving style. In addition, the demographic variables and driving styles of the participating drivers were considered. The variables 'Trial', 'Years Driving NL', 'Education Level', and 'Employment status' were excluded due to relatively low variation in the dataset. The remaining demographic variables were tested for multicollinearity. Figure 9 shows the correlation matrix between the demographic variables and the Pearson correlation coefficients, with only the statistically significant correlation cells being highlighted (p-value less than 0.05). If two variables were significantly and highly correlated, the one having a larger number of other correlated variables was removed. Based on this, the following variables were excluded: 'Knowledge AVs', 'Driving comfort NL', 'Anxious', 'Dissociative and Distress-reducing'.

The variables that were kept were: 'Gender', 'Age Group', 'Angry and Hostile', 'Patient and Careful', 'Trust_Tech', 'Trust AVs', 'Experience AV', 'AV appearance', 'AV driving style', 'Order of Scenario'. The 'Participant number' was also kept as a random intercept to account for repeated measures. Then, correlations with categorical variables were also tested. Table 6 presents the results. All the variables were retained.

	Driving Comfort NL	Trust Tech	Trust AVs	Knowledge AV	Experience AV	Anxious	Dissociative and Distress-reducing	Angry and Hostile	Patient and Careful
Driving Comfort NL	1.00								
Trust Tech		1.00							
Trust AVs		0.55	1.00						
Knowledge AV	0.45			1.00					
Experience AV	0.34			0.59	1.00				
Anxious	0.19		0.23	0.50	0.35	1.00			
Dissociative and Distress-reducing	-0.25	0.44	0.45			0.33	1.00		
Angry and Hostile	0.23			0.17	0.23	0.63	0.31	1.00	
Patient and Careful		0.61	0.49	0.18		0.18	0.48	0.22	1.00

1

-0.25

Figure 9. Correlation matrix between continuous demographic variables (only significant correlations displayed with the Pearson correlation coefficients).

Table 6. Correlations between participants related variables.

Variable 1	Variable 2	Test type	Result
Age Group	Gender	Chi-squared	Chi2 = 1.15, *p*-value = 0.56
Age Group	AV appearance	Chi-squared	Chi2 = 1.17, *p*-value = 0.56
Age Group	AV driving style	Chi-squared	Chi2 = 0.44, *p*-value = 0.8
Gender	AV appearance	Chi-squared	Chi2 = 0.03, *p*-value = 0.86
Gender	AV driving style	Chi-squared	Chi2 = 0.05, *p*-value = 0.83
Age Group	Trust in Technology	Kruskal Wallis	H-statistic: 0.07, *p*-value: 0.96
Age Group	Angry and Hostile	Kruskal Wallis	H-statistic: 0.57, *p*-value: 0.75
Age Group	Patient and Careful	Kruskal Wallis	H-statistic: 5.0, *p*-value: 0.08
Gender	Trust in Technology	Mann-Whitney U	U-statistic: 204.0, *p*-value: 0.19
Gender	Angry and Hostile	Mann-Whitney U	U-statistic: 355.5, *p*-value: 0.04
Gender	Patient and Careful	Mann-Whitney U	U-statistic: 245.5, *p*-value: 0.71

With the remaining variables, univariate linear mixed models were estimated. The best model was selected based on the combination of the following criteria: theoretical domain knowledge, importance of the variable, the significance (*p*-values) of the estimates, and the Akaike Information Criteria (AIC). Tables 7 and 8 present the coefficient estimates for the five parameters, using IDM and IDM+, respectively.

Table 7. Coefficient estimates of univariate linear mixed models for the five IDM-based car-following parameters (*p*-values in brackets).

	Jam spacing s0 (m)	Safe time gap T (s)	Max accel. alpha (m/s2)	Comfortable deceleration beta (m/s2)	Desired velocity v0 (km/h)
Intercept	7.35 (0.22)	−0.68 (0.73)	2.21 (0.02)*	0.38 (0.9)	107..51 (< 0.01)**
Participant factors:					
Gender: Female	1.12 (0.26)	0.58 (0.08)·	0.02 (0.92)	0.01 (0.98)	−2.71 (0.53)
Age: Middle aged 45–65	0.83 (0.49)	0.12 (0.76)	−0.16 (0.38)	0.01 (0.99)	−2.98 (0.57)
Age: Older 70+	4.1 (< 0.01)**	0.87 (0.03)*	0.18 (0.34)	−0.88 (0.15)	−11.5 (0.03)*
Driver driving style: Angry and Hostile	−0.91 (0.24)	−0.31 (0.22)	−0.09 (0.47)	0.55 (0.16)	−0.86 (0.8)
Driver driving style: Patient and Careful	1.13 (0.29)	0.53 (0.13)	−0.06 (0.74)	0.29 (0.58)	0.53 (0.91)
Trust in AVs	0.07 (0.95)	−0.54 (0.12)	0.13 (0.43)	−0.88 (0.13)	4.74 (0.32)
Lead vehicle factors:					
Appearance AV	−1.34 (0.05)*	−0.06 (0.79)	−0.02 (0.83)	0.23 (0.58)	−6.36 (0.04)*
Driving style AV	−0.35 (0.6)	0.06 (0.76)	−0.14 (0.2)	0.15 (0.71)	−3.75 (0.22)
Scenario order:					
Order: 2	−2.12 (< 0.01)**	0.08 (0.71)	0.05 (0.67)	−0.46 (0.26)	2.34 (0.44)
Order: 3	−0.72 (0.26)	0 (0.99)	−0.19 (0.07)·	−0.22 (0.58)	−1.61 (0.59)
Order: 4	−2.4 (< 0.01)**	0.08 (0.73)	0.06 (0.6)	−0.81 (0.07)·	−4.26 (0.2)
Interaction terms:					
Trust in AVs * Appearance AV	−1.69 (0.05)·	0.01 (0.98)	−0.06 (0.68)	1.01 (0.06)·	−4.13 (0.3)
Trust in AVs * Driving style AV	−0.69 (0.42)	0.16 (0.56)	0.12 (0.39)	−0.24 (0.65)	−2.97 (0.45)
Appearance AV * Driving style AV	1.35 (0.15)	−0.33 (0.27)	0.1 (0.51)	−0.47 (0.43)	1.72 (0.69)
Group variance for Participant ID: Intercept (Residual)	2.71 (2.99)	0.9 (0.94)	0.42 (0.49)	1.2 (1.9)	11.48 (14)
AIC	919.45	564.79	356.66	759.45	1392.07
Log-likelihood	−442.72	−265.39	−161.33	−362.72	−679.04

Significance level < 0.1; * < 0.05; ** < 0.01.

Tables 7 and 8 reveal some significant parameters at the significance levels < 0.1, < 0.05, and < 0.01. The AV appearance was found to reduce jam spacing and desired velocity. The interaction term with trust in AVs showed that when drivers have higher levels of trust in AVs, an AV appearance further reduces the jam spacing. Additionally, when the trust in

Table 8. Coefficient estimates of univariate linear mixed models for the five IDM+ based car-following parameters (p-values in brackets).

	Jam spacing s0 (m)	Safe time gap T (s)	Max accel. alpha (m/s2)	Comfortable deceleration beta (m/s2)	Desired velocity v0 (km/h)
Intercept	9.28 (0.13)	−1.48 (0.47)	2,39 (< 0.01)**	−1.05 (0.68)	94.65 (< 0.01)**
Participant factors:					
Gender: Female	0.97 (0.34)	0.68 (0.05)∗	−0.07 (0.62)	−0.17 (0.68)	−0.67 (0.87)
Age: Middle aged 45–65	0.85 (0.49)	0.28 (0.49)	−0.1 (0.55)	0.44 (0.38)	−0.89 (0.86)
Age: Older 70+	3.67 (< 0.01)**	1.11 (< 0.01)**	0.2 (0.26)	−0.3 (0.56)	−9.71 (0.06)·
Driver driving style: Angry and Hostile	−0.91 (0.25)	−0.21 (0.42)	−0.06 (0.59)	0.44 (0.19)	2.85 (0.38)
Driver driving style: Patient and Careful	0.79 (0.47)	0.7 (0.06)·	−0.09 (0.56)	0.49 (0.28)	−1.43 (0.75)
Trust in AVs	0.22 (0.84)	−0.6 (0.1)	0.01 (0.93)	−0.56 (0.29)	3.94 (0.4)
Lead vehicle factors:					
Appearance AV	−1.56 (0.03)∗	0.1 (0.66)	−0.09 (0.46)	0.37 (0.39)	−1.55 (0.64)
Driving style AV	−0.24 (0.73)	0.08 (0.72)	−0.08 (0.48)	0.57 (0.18)	−3.66 (0.27)
Scenario order:					
Order: 2	−2.5 (< 0.01)**	0.06 (0.77)	0 (0.98)	−0.46 (0.28)	4.59 (0.16)
Order: 3	−0.85 (0.21)	−0.18 (0.4)	−0.19 (0.1)·	−0.24 (0.56)	−4.13 (0.2)
Order: 4	−2.82 (< 0.01)**	0.04 (0.87)	0.07 (0.59)	−1.04 (0.02)∗	0.29 (0.93)
Interaction terms:					
Trust in AVs ∗ Appearance AV	−1.25 (0.17)	0.09 (0.77)	0.04 (0.8)	0.7 (0.21)	−1.16 (0.79)
Trust in AVs ∗ Driving style AV	−1.37 (0.12)	0.13 (0.65)	0.09 (0.55)	−0.53 (0.34)	−7.15 (0.09)·
Appearance AV ∗ Driving style AV	1.45 (0.14)	−0.4 (0.22)	0.08 (0.6)	−0.98 (0.11)	−1.62 (0.73)
Group variance for Participant ID: Intercept (Residual)	2.74 (3.13)	0.91 (1.03)	0.36 (0.53)	0.84 (1.95)	10.39 (15.03)
AIC	931.35	588.04	365.27	752.45	1405.21
Log-likelihood	−448.67	−277.02	−165.63	−359.23	−685.61

Significance level < 0.1; ∗ < 0.05; ∗∗ < 0.01.

AVs was higher, an AV appearance also resulted in larger comfortable deceleration. As for personal characteristics, older drivers tended to have larger jam spacing, larger safe time gap, and smaller desired speeds compared to younger drivers. Female drivers had larger safe time gaps than male drivers. As for driving style, drivers with a greater inclination to patient and careful driving styles had larger safe time gaps. Finally, the group variance for Participant ID is significant, showing that significant differences were observed between participants at the level of the subjects which the mixed model correctly considered. The order of the scenarios also played a role. Scenarios with Order 2 show smaller jam spacing compared to Order 1. Scenarios with Order 3 saw smaller max acceleration, and scenarios with Order 4 saw smaller jam spacing and smaller comfortable deceleration compared to Order 1. In the next section, we discuss the main implications of all these results.

6. Discussion and limitations

To understand the effects of mixed traffic factors on the car-following behaviour of HDVs, we collected car-following data using a driving simulator experiment and estimated univariate linear mixed regression models for the parameters of the IDM car-following model and IDM+. This provided insight into the precise magnitude and direction of the effects of mixed traffic factors on each of the car-following parameters. We combined the insights from both models to understand the impacts of the various mixed traffic factors, as well as drivers' personal characteristics on the car-following model parameters. In this section, we discuss the results in line with the research questions that were defined and the literature, including the limitations.

6.1. What is the effect of mixed traffic factors on the car-following behaviour of HDVs, as reflected by car-following model parameters?

Three factors are attributed to mixed traffic conditions, namely, the *Vehicle appearance* (AV or HDV), the *Vehicle driving style* (AV or HDV), and *trust* in AVs. Significant effects were observed for these factors on jam spacing, comfortable deceleration, and the desired speed. When the AV was recognisable as AV (i.e. appearance AV), then the participants maintained smaller jam spacing (smaller by around 1.5 m) compared to the scenarios in which the lead vehicle was recognisable as HDV. This means that drivers are comfortable keeping a closer distance to the AV compared to the HDV when in standstill, suggesting higher trust in AVs. Also, for scenarios where the AV was recognisable, the median safe time gap for the IDM was smaller than in scenarios where the AV was not recognisable (the median safe time gap was smallest for the scenario AV AV). Even though this did not turn out to be statistically significant in the model, it is still worth mentioning it as such an effect was also observed in previous literature (Wen, Cui, and Jian 2022; Zhao et al. 2020). For example, Zhao et al. (2020) also found that those who trust AVs more maintain a shorter following distance with the AV leader. The fact that drivers keep a closer distance due to higher trust is supported by the observation that when the trust in AVs was higher, the jam spacing was further reduced (by around 2 m). While AV appearance reduced the jam spacing, it also reduced the desired velocity (by approx. 6 km/h). This finding is interesting as it would be expected that higher trust would lead drivers to drive faster when following a lead vehicle. However, this is not the case because in the experiment, drivers were constrained by the lead vehicle and could not overtake. Therefore, it is possible that drivers thought AVs had a more conservative driving style (AVs in the experiment were designed to be more conservative when they followed AV driving style). Drivers having greater trust in AVs also had a further smaller desired velocity (by approx. 7 km/h) when the vehicle had an AV driving style (more conservative). These findings are consistent in supporting the explanation that drivers perceived AVs as safe and conservative. Therefore, they were more comfortable keeping a close distance (indicated by smaller standstill distance), but when constrained (due to lack of opportunity for overtaking), they had smaller desired velocities.

Another finding was that when trust in AVs was higher, it resulted in a larger comfortable deceleration when the vehicle had an AV appearance (by about 1 m/s^2). This suggests that drivers had higher braking magnitudes when following an AV appearing vehicle than when following an HDV appearing vehicle. This result is in line with the smaller jam distance, as if drivers follow AVs closer, then it is likely that they will brake harder. This also points to some traffic safety implications. A connection can be made with the study on real-world crashes between AVs and HDVs, which found that most crashes occur when an HDV is following an AV that comes to a stop (Xu et al. 2019).

Another interesting finding was that the variance in the parameters of desired speed and time headway was significantly smaller in the AV AV scenario compared to the HDV

HDV or HDV AV scenarios. This indicates that drivers drive more homogenously when in traffic having recognisable AVs.

A nuance must be made here with respect to the desired speed. For the same model, there were differences observed in desired speed parameter between the scenarios. This could appear unnatural as a driver's desired speed when in free flow should be independent of the type of vehicle driving in front. Still, we found differences. This suggests that drivers may, at least, temporarily, have different desired speeds as a consequence of how they perceive the lead vehicle. This could be similar to the effect that drivers may wish to drive at higher than their normal speeds when following a slow-moving vehicle.

6.2. What is the effect of driver-related factors on the car-following behaviour of HDVs, as reflected by car-following model parameters?

As for personal characteristics, age, gender, and driving style influenced some of the car-following parameters. Compared to younger drivers, older drivers had significantly larger jam spacing (by about 4 m), larger safe time gap (by about 1 s), and lower desired speed (by about 10 km/h). These show that older drivers had a more conservative/less aggressive driving style than younger drivers. These findings are consistent with existing literature (Cantin et al. 2009; Singh and Kathuria 2021). Female drivers had significantly larger safe time gaps (by about 0.6 s) than male drivers, indicating a less aggressive driving style, which is also as anticipated in literature (Zolali, Mirbaha, and Saffarzadeh 2022). Considering the driving style, drivers having a larger tendency of patient and careful driving style had significantly larger safe time gaps (by about 0.7 s), which is also as would be expected. Finally, a note on the effect of scenario order, even though it is not relevant for mixed traffic specifically but provides an insight into the learning effect. The jam spacing was smaller in Order 2 and Order 4 (both by about 2.5 m) compared to Order 1. This can be attributed to becoming more familiar and comfortable in the simulator environment (Colonna et al. 2016). In Order 3, a smaller maximum acceleration was noticed as compared to Order 1 (by about 0.2 m/s2).

In the car-following section, drivers drove based on the experience /expectations they had gained from driving in mixed traffic in the prior route. Therefore, the car-following section measured what could be termed as the behaviour based on learning or developed expectations. It is possible that drivers could behave differently if they had closer and longer interactions with AVs specifically and could observe the way the AV was following its leader in the car-following section (Aramrattana, Fu, and Selpi 2022; Razmi Rad et al. 2021; Schoenmakers, Yang, and Farah 2021). Moreover, all observed behaviour depends on the setup of the experiment. Particularly, the way we defined AV driving behaviour would directly affect how participants perceive and interact with the AVs. In real life, however, AVs have different driving styles, which are also different between different manufacturers. Also, general limitations applicable to driving simulator studies concerning their realism and validity also apply to the results of this research.

While the above results and discussion (including the previous research question) are in light of the model results, it must not be taken directly that the factors having statistically insignificant effects will have no effects on driving behaviour. It is certain that with further research and more data, deeper insights into their effects can be gained. For example, it may be that the model shows that vehicle appearance has a significant effect on desired velocity. However, it is still possible that this also results in a change in safe time gap, which is not captured in the model. But the differences in these parameters can be observed in the descriptive overview across the scenarios. For example, the safe time gap in comparison to the HDV HDV scenario was: 0.45 s smaller for the AV AV scenario, 0.18 s smaller for the AV HDV scenario, and almost equal to the HDV AV scenario. Therefore, the AV being recognisable resulted in a reduction of the safe time gaps. This, of course, needs to be statistically tested with future research. Additionally, while these results provide useful insights into the drivers' behaviour in mixed traffic, it leaves an open question of whether the observed behaviour remains unchanged over time. For this, a longer-term study is needed.

6.3. Caveat on comparing similar models

There are many popular models available to describe car-following behaviour. In our study, we selected the IDM and IDM+. Both models having the same parameters helped to reveal the differences between them, thus isolating the implications of model formulation. We presented the differences in the estimates between the IDM and IDM+ for each scenario, in addition to the parameter estimates. Notable differences were mainly observed for the parameters of the safe time gap and desired velocity. While our focus in this study was not to perform a rigorous comparison of different car-following models, we acknowledge that IDM and IDM+ are conceptually close and do not capture the full range of possible behavioural mechanisms. Models with fundamentally different underpinnings, such as Gipps (Gipps 1981), Newell's model (Newell 2002), or psychophysical approaches (Hamdar, Mahmassani, and Treiber 2015; Wiedemann 1974), may provide further insights by capturing safety constraints, response delays, or perception thresholds. In addition, data-driven models (e.g. machine learning) can capture complex nonlinear patterns beyond rule-based models (Pan et al. 2023; Shi et al. 2021; Soldevila, Knoop, and Hoogendoorn 2021). A more robust way to compare the impacts of mixed traffic would therefore be to implement and contrast a diverse set of models, thereby revealing a broader spectrum of possible outcomes. Future work should extend this to models with different behavioural foundations.

A second caveat to be raised in this context is the goodness of fit measure. The goodness of fit (RMSE) was mostly the same between the IDM and IDM+. However, it is important to note that while RMSE is a commonly used goodness-of-fit measure, it only reflects the point-wise differences between observed and predicted values and does not fully capture differences in car-following patterns and dynamics (e.g. oscillations, lag effects, or acceleration patterns). This can explain why IDM and IDM+, despite differences in formulation, yielded similar RMSE values. Other measures such as the Dynamic Time Warping (DTW) used by Taylor et al. (2015) can better capture the behavioural differences in reaction timing, smoothness, and acceleration patterns.

A final caveat must be noted here on the reason why the two models provide different desired velocity values. This has to do with how the desired velocity parameter plays a role in the calibration of the models. The IDM+ has a constraint that puts a limit on acceleration, which makes it more conservative than the IDM. The IDM, not having this constraint, can produce higher desired velocities. Therefore, the desired velocity parameter should not be strictly viewed as representing the true velocity at which drivers would like to drive at free-flow, but more as a parameter that compensates for the errors or artefacts in the model. Similarly, differences in other parameters between the two models has primarily to do with the model mechanism. Hence, the parameters should not be taken out separately and applied as they are defined, but they should be used together with the model context where they belong.

7. Potential applications & recommendations

This section discusses possible applications of this research for potential stakeholders and recommendations for future research.

7.1. Potential applications

Researchers can use the findings of this study to see how factors such as mixed traffic conditions, demographics, and driving style influence HDVs' car-following behaviour, and to decide which of these factors are most relevant to include (or exclude) in their own work. The estimated parameters of the IDM and IDM+ for different mixed traffic conditions can be directly implemented for modelling car-following behaviour in various types of studies. For instance, they can be implemented in simulation studies focusing on mixed traffic to gain insights into the implications for traffic safety and efficiency.

Vehicle licensing authorities interested in setting functional and operating standards for AVs can use the insights in this study to understand what factors related to mixed traffic affect HDVs. This could help in making decisions on setting functional and operational standards for AVs.

Vehicle manufacturers can benefit from the insights of this study for the design and development of their AVs in two ways. First, they can make better informed decisions on aspects such as the appearance and driving style of their AVs by understanding the potential impacts on HDVs.

Driving license authorities and driving schools can use the findings of this study to not only understand how human drivers' car-following behaviour is affected in mixed traffic, but also in the training of drivers to make them more aware of their driving and how they can be affected in mixed traffic.

7.2. Recommendations for future research

Firstly, we recommend some good practices that we incorporated in this study for future research too. For instance, defining a 'complete trajectory' for the lead vehicle and using standard best practices for estimating car-following models in terms of using the measure of performance (using spacing) and goodness of fit (using RMSE) measures allows both a more correct investigation approach and meaningful comparisons of future studies. Secondly, going beyond studying drivers' car-following behaviour in a single driving simulator experiment, it would be insightful to study the behaviour and change in behaviour over a longer term. This would allow a more long-term, robust understanding of the way mixed traffic affects HDV car-following behaviour. Third, collecting data from field tests or naturalistic driving studies would allow validation of the findings of this study and potentially lead to new findings. Fourth, different appearances and driving styles of AVs could be tested to see how that affects HDV car-following behaviour, providing a more comprehensive understanding. Fifth, while we used the IDM and IDM+, other car-following models can also be tested to firstly create a wider collection of usable car-following models for mixed traffic, and secondly allow a broader comparison of the choice of models. Sixth, in addition to estimating parameters of existing car-following models, future research can attempt to modify existing models or design new models to capture mixed traffic impacts through different mechanisms. Seventh, models for other behaviours, such as lane changing models or integrated models (car-following + lane changing), can be estimated to provide exhaustive possibilities to investigate and model HDV behaviour in mixed traffic. This could be especially relevant when there are multiple lanes, allowing drivers to overtake the AV. Therefore, different behaviours on different road types would also be an important research direction. Finally, implementing the developed behavioural and mathematical models that characterise these interactions in microscopic traffic simulation would enable evaluating the impacts on traffic flow efficiency, safety, and emissions (Ard et al. 2020; Makridis et al. 2020; Raju and Farah 2021; Stogios et al. 2019).

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