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Emerging Behavioral Adaptation of Human-Driven Vehicles in Interactions with Automated Vehicles: Insights from a Microsimulation Study

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Abstract

Automated vehicles (AVs) are expected to shape the future of transportation and to improve traffic flow and safety. Studies have focused on AVs effects on traffic flow during the transition to full automation, with few examining their influence on human-driven vehicles (HDVs). This study investigated potential changes in HDVs' driving behavior induced by the presence of AVs with different driving styles (aggressive vs. cautious) at varying market penetration rates (MPRs) (0%, 25%, 50%, and 75%). First, a driving simulator experiment with 160 people (56 females, 104 males) was conducted to collect HDV trajectory data. Then, a microsimulation model was implemented in VISSIM, where HDV behavioral parameters were calibrated using the driving simulator data. Average time headway (THW), relative velocity (RelVel), average acceleration (Acc), average deceleration (Dec), and lane change frequency (LnCh) were used as behavioral metrics. A two-way ANOVA was applied for analysis. Results showed that higher AVs' MPRs decreased THW, Acc, and Dec in HDVs, while RelVel increased with cautious AVs and decreased with aggressive AVs. Similar trends were observed for LnCh. These findings highlight the need to consider potential HDVs behavioral adaptation during the transition phase, as neglecting it may lead to inaccurate traffic assessments and ineffective policies.

Keywords: behavioral adaptation; driving simulator; VISSIM; mixed traffic; car following; microsimulation analysis; smart mobility

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1. Introduction

Automated vehicles (AVs), equipped with sophisticated technological capabilities, are believed to shape the future of transportation and transform current traffic trends into safer and smoother systems [1,2]. However, the advantages of these promises depend on the extensive implementation of AVs, as at low penetration rates, referred to as the transition phase, when human-driven vehicles (HDVs) largely operate in the network, the impact of AVs is minimal [1–4].

The shift to completely automated traffic situations will be somewhat prolonged due to the requisite infrastructure and technical advancements necessary for the extensive deployment of highly AVs [5,6]. These vehicle types are classified into six categories by the Society of Automotive Engineers (SAE) based on their performance and driving tasks. According to this classification, HDVs are classified as Level 0 when lacking automation, Level 1 denotes driver assistance, Levels 2 and 3 represent partial and conditional AVs, while Levels 4 and 5 signify highly and fully automated or connected AVs (CAVs), respectively [7].

With the availability of commercial Level 2 and Level 3 AVs in the market and the increasing interest in using these vehicles, the transition phase has already started. A prevalent element of these AVs is adaptive cruise control (ACC), which allows drivers to set and maintain a safe distance from the vehicle ahead [8,9]. However, the driving styles of human drivers varies due to effects of their psychological and biological characteristics [10,11]. These differences, in turn, shape their preferences for AVs' driving styles, with human drivers tending to prefer AVs that either mirror their own style or adopt a more defensive driving approach [9]. Consequently, ACC headway configurations in AVs are designed to somewhat improve their acceptability and enhance user satisfaction by accommodating diverse driving styles through a broad range of adjustable headway settings.

The broad range of ACC headway settings in AVs complicates the mixed traffic flow of AVs and HDVs during the transitional phase, whereby conventional vehicle drivers and AVs with different driving styles interact. The intrinsic differences in the behavior of HDVs and their fellow AVs may influence human drivers' behavior, hence exacerbating the complexity of mixed traffic flow. Therefore, it is important to examine the possible changes in human drivers' behavior while interacting with AVs of different driving styles at varying market penetration rates (MPRs).

2. Review of Existing Literature

Prior studies have investigated mixed traffic comprising AVs and HDVs from the following two principal perspectives: (1) the network-level perspective and (2) the individual-level perspective, primarily emphasizing the viewpoint of human drivers.

2.1. Network-Level Impacts of Mixed Traffic

Studies focusing on the mixed traffic flow of AVs and HDVs utilized microsimulation methodology as a helpful tool to simulate the gradual increase in the penetration rates of AVs and its influence on traffic efficiency at the network level throughout the transition phase. They simulated various types of AVs and CAVs and evaluated their impacts on traffic performance, safety, and environmental outcomes under mixed traffic conditions.

Manjunatha et al. [12] simulated the behavior of AVs and CAVs based on literature findings and reported that while CAVs considerably reduce delays and improve travel time and speed, they do not reduce emissions, and AVs without connectivity fail to achieve these improvements. Gemma et al. [13] modeled CAVs based on their assumptions and found these AV types are effective in congested traffic situations and improve road capacity and average speed. Sekar et al. [14], relying on VISSIM default behavioral parameters for AVs, concluded that cautious AVs reduce both travel time and safety risks.

Focusing on the driving styles of AVs, Aria et al. [15] simulated AVs to drive aggressively based on the recommended behavioral parameters by the literature and reported that AVs increase average density by 8.09%, travel speed by 8.48%, and reduce travel time by 9% during peak hours, thereby improving both traffic performance and safety. Szimba and Hartmann [16] modeled AVs based on their assumptions and reported that Level 4 and Level 5 AVs improve travel time by 20% and 27%, respectively. Similarly, Ma et al. [17] reported that AVs positively affect traffic flow and reduce average travel time, with CAVs outperforming Level 2 AVs in improving travel time.

In addition, Lu et al. [18] utilized real-world data to model the behavior of AVs in their study. They found that AVs with cautious, normal, and aggressive driving styles show different speed distributions, with aggressive AVs resulting in higher speeds and smaller travel times. Similarly, Saljoqi et al. [19] simulated AVs of different driving styles considering the real-world driving styles of the AVs' users and found that Level 2 AVs increase travel time (1.08–4.09%), delay (13.22–99.28%), and slightly improve flow rate (0.09–0.26%). Likewise, Shang and Stern [20], evaluating the impacts of theoretical and commercially available AVs (Level 2) on traffic flow, found that while theoretical AVs improve capacity by up to 7%, Level 2 AVs may reduce capacity by as much as 35%.

Since the performance of the whole traffic network is made up of countless local interactions, it may be essential to move beyond the large perspective. Therefore, the following section examines the interactions between HDVs and AVs on a smaller scale, evaluating the dynamics of individual interactions between them. These studies give us a better idea of the social and behavioral mechanisms that ultimately shape network-level outcomes.

2.2. Individual-Level Impacts of Mixed Traffic

The individual interactions between HDVs and AVs have been studied mostly using driving simulators or field experiments. Researchers have primarily focused on the individual interactions of these two vehicle types to analyze the car-following behavior of human drivers due to its critical effect on traffic flow and safety [21,22].

In a field experiment involving one AV and one HDV and focusing on the car-following behavior of drivers, Rahmati et al. [23] found that human drivers follow an AV closer with a shorter distance as compared to an HDV. Wen et al. [24], utilizing the Waymo Open Dataset and focusing on the car-following behavior of drivers in their interactions with AVs, reported that, although the average time headway of human drivers behind an AV is smaller as compared with an HDV, their acceleration and speeding behaviors improved when following the AV. Similarly, Mahdinia et al. [25] in a field experiment found that human drivers show a smoother acceleration and speeding behavior behind an AV compared to an HDV, improving driving stability.

Similar results have been reported by the studies using driving simulator experiments. Jo et al. [26] modeled an AV and an HDV with different driving logics to study the behavior of human drivers in interaction with one AV and one HDV under different scenarios. They found that the behavior of human drivers varied when following the AV as compared to the HDV. They tend to decrease their maximum acceleration and average deceleration behind the AV by 44.45% and 4.89%, respectively. Addressing the safety aspect of interactions between AVs and HDVs, Chand et al. [27] found that human drivers experienced lower stress levels when following an AV compared to an HDV, resulting in safer interactions and fewer accidents.

A limited number of studies have gone beyond examining one-on-one interactions between AVs and HDVs, instead have focused on the social interactions of human drivers with AVs at various MPRs during the transition phase. These studies employed driving simulator experiments to observe human drivers' behavior when interacting with AVs in virtual environments. Aramrattana et al. [28] found that 90% of human drivers adapted their driving behavior when driving among AVs compared to HDVs. Stange et al. [29] studied the behavior of human drivers when driving among a mixed traffic of cautious AVs (with minimum time headway of 2.75 s) and HDVs (with minimum time headway of 1.2 s). They increased the MPRs of AVs from 0% to 75% with an increment of 25% and found that human drivers decreased their average time headway and average speed as the MPR of AVs increased. Similarly, de Zwart et al. [30] modeled AVs with an aggressive driving style (minimum time headway: 0.5 s), while HDVs exhibited more defensive behavior (minimum time headway: 1.1 s). They examined human driver behavior under three AV

MPRs (0%, 50%, and 100%) and found that, as the MPR of AVs increased, human drivers tended to maintain a smaller average time headway and reduce their relative speed.

Research on the behavioral adaptation of human drivers during the transition phase offers valuable insights into the field. However, researchers' reliance on assumptions about AVs' behavior, coupled with the neglect of variability in HDVs' behavior, may influence the validity and accuracy of the outcomes. Therefore, further studies incorporating a wider range of behavioral metrics are needed to better understand how HDVs adapt their driving behavior when interacting with both aggressive and cautious AVs at varying MPRs.

3. Objectives and Contributions

This study aimed to examine the driving behavior of HDVs when interacting with AVs at varying MPRs, ranging from 0% to 75% in 25% increments and different driving styles (aggressive vs. cautious), within a microsimulation context. Average time headway (THW), relative velocity (RelVel), average acceleration (Acc), average deceleration (Dec), and the lane change frequency (LnCh) of HDVs were used as indicators of driving behavior.

More specifically, the study offers the following contributions to the field:

- Simulating AVs' behavior based on their practical capabilities rather than relying on assumptions;
- Modeling HDVs' behavior using observed data from simulations to account for the heterogeneity in the driving behavior of human drivers;
- Examining the behavioral adaptation of HDVs during interactions with both aggressive and cautious AVs across varying MPRs.

The study addresses the following two research questions:

- RQ1: Does the presence of AVs cause HDVs to adapt their driving behavior when interacting with AVs at varying MPRs?
- RQ2: To what extent do the driving styles of AVs (i.e., aggressive vs. cautious) influence the driving behavior of HDVs?

Based on the findings of previous studies, we hypothesized that with the increase in the MPR of AVs, HDVs adapt their driving behavior by maintaining a smaller THW (H1), decreasing RelVel (H2), decreasing Acc (H3), reducing Dec (H4), and reducing LnCh (H5).

Moreover, we expect that these adaptations will be influenced by the driving style of AVs; cautious AVs, by maintaining larger gaps and providing more predictable environment for HDVs maneuvers, may result in more significant reductions in these behavioral indicators, as HDVs are likely to follow them more closely and with reduced necessity for abrupt maneuvers. Conversely, aggressive AVs may cause fewer significant changes in HDVs' behavior, as their more assertive driving behavior requires that HDVs keep larger safety margins.

4. Materials and Methods

The study used both a driving simulator and a microsimulation tool to examine the evolution of human drivers' behavior during interactions with AVs. VISSIM 25 (SP 0.7), a powerful and widely used microsimulation software for assessing AVs' behavior [31], was used to analyze the behavior of HDVs under various scenarios. The software allows the calibration of ten behavioral parameters (CC0–CC9), which requires detailed trajectory data for the calibration purposes. Calibrating all of these parameters is essential, as they interact with one another [32]. Therefore, we employed the driving simulator tool, which provided detailed trajectory information on the spacing and speeding behavior of HDVs, enabling the calibration of all relevant behavioral parameters in VISSIM, so that more realistic results could be obtained.

4.1. Driving Simulator Experiment

4.1.1. Participants

A total of 178 participants were recruited, of whom 18 participants withdrew from the experiment due to motion sickness, leaving 160 people (56 females and 104 males) who completed the driving simulator experiment. All participants held a valid Italian driving license, had at least one year of driving experience, and lacked prior experience in driving simulator experiments. The participants' ages ranged from 19 to 65 years (mean = 25.7 years, SD = 7.8 years). The experimental procedure received approval from the Ethics Committee of the Human Inspired Technology (HIT) Research Center at the University of Padua (ID: 2023_223R3).

4.1.2. Apparatus

The experiment was performed at the Transportation Laboratory of the University of Padua utilizing a dynamic driving simulator developed by STSoftware® (Figure 1). The simulator features a cockpit with an adjustable car seat and a gaming steering wheel that provides dynamic force feedback and allows a 900-degree rotation, accompanied by gas, brake, and clutch pedals.

Figure 1. Configuration of the driving simulator.

It is operated by three networked computers and uses five full HD screens (1920 $\times$ 1080 pixels each) to provide a 330° horizontal and 45° vertical sight range. Additionally, it is equipped with a Dolby Surround® sound system consisting of three front speakers, two rear speakers, and a subwoofer. The validity and reliability of the driving simulator have been supported by prior investigations [33,34], and it effectively simulated the mixed traffic flow of AVs and HDVs [35].

4.1.3. Experiment Environment and Traffic Conditions

The participants' car-following data were collected on a 12 km straight highway segment with two lanes, each 3.75 m wide. A one-meter median divider was used to separate the oncoming traffic flow. The participants were asked to drive, as they would in the real world, allowing them to perform lane changes and overtaking maneuvers during the experiment. The total duration of the experiment varied between 12 and 15 min depending on the participants' driving speed. The speed limit varied during the experiment, with the first 5 km and the last 4 km at a speed limit of 130 km/h and the 3 km middle segment of the roadway at a speed limit of 100 km/h.

Data from the initial 2 km were excluded from analysis, because this part was considered to enable participants to attain their desired speed, and the final 0.5 km was omitted to prevent behavioral deviations near the end of the route.

To address the heterogeneity of human drivers in simulating HDVs, empirical time headway data were collected on a weekday from a two-lane highway segment in the Veneto region of Italy. The chosen time headways for HDVs varied from 0.3 s to 2.73 s, with a mean of 1.33 s, optimally modeled by a Johnson SB distribution due to its improved goodness-of-fit relative to other distributions. The maximum velocity of HDVs was represented using a uniform distribution within ±10 km/h of the designated speed limit. Furthermore, a moderate traffic flow of 2400 vehicles per hour was simulated to replicate realistic highway conditions and ensure consistent car-following interactions during the experiment.

4.2. Microsimulation Analysis

The trajectory data obtained from the driving simulator experiment, recorded at a frequency of 50 Hz and containing detailed information on participants' speed and spacing behaviors, were used to calibrate HDVs' car-following behavior in VISSIM. The software provides a wide range of behavioral parameters for the calibration of vehicles' behavior, requiring highly detailed data for an accurate calibration. The trajectory data obtained from our driving simulator experiment offered the proper detail for this, but real-world data frequently lacked the appropriate detail for calibration of all behavioral parameters. In the simulation, the car-following behavior of HDVs and AVs agents was modeled by two distinct car-following models.

4.2.1. Modeling the Behavior of HDVs

The car-following behavior of the participants from the driving simulator experiment was analyzed based on the Wiedemann's 99 car-following model provided in VISSIM. As a psycho-physical model, it controls a vehicle's acceleration and deceleration based on the driver's perception of changes in relative speed and distance to the vehicle ahead [36,37]. In VISSIM, ten calibration parameters (CC0–CC9) are available for modeling vehicles' car-following behavior. A detailed explanation of these parameters is given in [38]. We adopted the same approach as described in [39] for extracting these parameters, with the exception that CC1 was modeled using a distribution derived from observed data in the driving simulator experiment rather than a fixed value. Moreover, the desired speed distribution was defined based on the participants' observed speeds in the driving simulator experiment under conditions where no leading vehicle was present. Table 1 presents the values used for each parameter.

Table 1. Calibrated behavioral parameters used in the simulation.

Parameter	Default Value	Calibrated Value
CC0	1.50 m	1.50 m
CC1	0.90 s	Empirical distribution (median: 0.91 s)
CC2	4.00 m	1.34 m
CC3	−8.00 s	−6.57 s
CC4	−0.35 m/s	−0.98 m/s
CC5	0.35 m/s	1.05 m/s
CC6	11.44 L/m.s	4.22 L/m.s
CC7	0.25 m/s^2	0.49 m/s^2
CC8	3.50 m/s^2	1.28 m/s^2
CC9	1.50 m/s^2	0.83 m/s^2

4.2.2. Modeling the Behavior of AVs

The available adaptive cruise control (ACC) car-following model in VISSIM was employed to simulate AVs' behavior. This model governs the longitudinal movement of vehicles, mimicking a typical ACC system that adjusts based on the distance to the leading vehicle, with deterministic behavior. It ensures smooth and safe acceleration and deceleration depending on the lead vehicle's movement. The model allows the configuration of a desired distance, representing the ACC headway setting, which determines the preferred time headway for AVs. Among its 16 calibration parameters, we used Min_gap_time to represent the desired headway. A time headway of 1 s was applied to simulate aggressive AVs, as this is the minimum setting offered by many commercially available ACC systems [40,41], while a 3 s headway was used for cautious AVs, reflecting the maximum preferred headway by ACC users [42]. These two driving styles were used because they are widely used extreme end-points for AV driving style in human-AV studies when examining trust, acceptance, comfort, and takeover behavior of human drivers [43–45]. Additionally, the maximum desired speed for AVs was set to 130 km/h, aligning with the speed limit, as AVs are expected to strictly adhere to traffic regulations. Further details on the ACC model and its parameters can be found in [46].

4.2.3. Simulation Setup and Procedure

A 12 km two-lane one-way highway segment was implemented in the simulation, mirroring the network used in the driving simulator experiment. The analysis was based on the results of ten simulation runs, each lasting one hour (excluding the 30 min warm-up and cooldown periods), conducted under four AV MPRs (0%, 25%, 50%, and 75%) and two AVs' driving styles (cautious and aggressive). The total traffic flow of HDVs and AVs was set to simulate LOS D traffic conditions. Table 2 illustrates the simulation scenarios.

Table 2. Simulation scenarios.

Scenario	MPR of AVs	AVs' Driving Style
S1	0%	-
S2	25%	Aggressive
S3	50%	Aggressive
S4	75%	Aggressive
S5	25%	Cautious
S6	50%	Cautious
S7	75%	Cautious

4.3. Analyzed Variables

To examine the behavior of HDVs when interacting with AVs of different driving styles under various MPRs, several behavioral indicators were evaluated. These included average time headway (THW), relative velocity (RelVel), average acceleration (Acc), average deceleration (Dec), and the frequency of lane change (LnCh) for each HDV. Most of these metrics are commonly employed in the literature to assess how human drivers adapt their driving behavior in the presence of AVs [23,25,29,30,47]. THW represents the spacing behavior of HDVs, which is a critical behavioral indicator with safety implications [48]. Under free-flow traffic conditions, variations in drivers' velocity are minimal [49], whereas in congested traffic, drivers are restricted by the surrounding vehicles, and their RelVel with respect to the leading vehicle has a significant role in determining their driving safety and stability [50,51]. Thus, using the RelVel metric indicates the smoothness of drivers' speed adjustment behavior. Furthermore, research has shown that drivers' acceleration and deceleration behavior influence both traffic flow [52,53] and traffic-related emissions [54]. Therefore, we used Acc and Dec to examine how the increase in MPRs of AVs on average can affect the acceleration and deceleration behavior of HDVs. The LnCh indicator was used due to its correlation with the driving aggressiveness [55] and safety [56], providing useful insights in understanding the potential shifts in driving behavior of HDVs induced by the increasing MPRs of AVs. The data for these variables were collected under traffic conditions equivalent to LOS D, as behavioral parameters are more pronounced and informative when traffic flow operates near roadway capacity rather than free-flow conditions.

4.4. Statistical Analysis

The continues dependent variables were analyzed applying a two-way ANOVA, with MPR and the driving behavior of AVs as factors. The statistical analyses were performed employing R 4.5.1 statistical software [57] at the significance level of $\alpha = 0.05$.

For each dependent variable, the assumption of normality was checked using QQ plot diagnostics. To improve the strength of the analyses, a Box–Cox transformation [58], a well-established technique for stabilizing variance and improve normality of residuals in parametric models [59], was applied to the dependent variables before fitting ANOVA, as the assumption of normality was not met. This method was used, as it allowed for testing the interaction effects of the independent variables with the possibility to plot the results of the model, while with a nonparametric alternative, such as aligned ranked transform ANOVA [60], the plot will be based on raw data for better interpretability, which are prone to misinterpretation due to skewness and non-homogenous variances. After transforming the data, the ANOVA model was re-run, which resulted in residuals that followed a normal distribution. Subsequently, the marginal means were converted back to their original scale to ensure easier interpretation.

The analysis was conducted separately for each dependent variable and included estimating the partial eta squared (${\eta_p}^2$) effect size. An ${\eta_p}^2$ value between 0.01 and 0.06 is considered a small effect, values from greater than 0.06 up to 0.14 indicate a medium effect, and values exceeding 0.14 represent a large effect [61].

A post hoc analysis was conducted using Tukey's HSD adjustment with an estimated Cohen's d effect size (d). The effect size d was interpreted according to conventional thresholds; values around 0.2 indicate a small effect, around 0.5 a medium effect, and 0.8 or higher a large effect [61]. This approach allowed for pairwise comparisons between groups while controlling for Type I error, ensuring robust and meaningful interpretation of the differences observed.

It should be noted that the amount of data available was very large, as observations were collected for all vehicles across the ten simulation runs for each variable analyzed. As a result, the statistical power of the analysis was very high. This implies that the ANOVA could detect statistically significant differences even when the actual differences were minimal and negligible in practical terms. In such contexts, it is therefore more appropriate to interpret and discuss the results primarily in terms of effect sizes rather than p-values [62].

5. Results and Discussion

5.1. Effect of AVs on the Average Time Headway of HDVs

As indicated in Table 3, the results of the two-way ANOVA for the dependent variable of THW showed a main effect of AVs' MPR [$F(3, 115{,}424) = 1776.439$, $p < 0.001$, ${\eta_p}^2 = 0.044$] with a small-to-medium effect size. Similarly, the main effect of AV behavior [$F(1, 115{,}424) = 9.986$, $p < 0.001$, ${\eta_p}^2 < 0.001$] and its interaction with AVs' MPR [$F(3, 115{,}424) = 14.836$, $p < 0.001$, ${\eta_p}^2 < 0.001$] was significant with negligible effect sizes. This suggests that changes in THW of HDVs in their interactions with AVs are minimally influenced by the driving styles of AVs.

As shown in Figure 2, HDVs significantly decreased their THW when interacting with both aggressive and cautious AVs. The pairwise comparisons, as provided in Table 4, showed that, as the MPR of AVs, regardless of their driving styles, increased, HDVs decreased the THW with effect sizes ranging from small to medium. In addition, the difference in THW of HDVs during interactions with aggressive and cautious AVs was significant only at an MPR of 75% (mean difference = 0.035, t = 7.036, p < 0.001, d = 0.134), with small-to-medium effect sizes.

Table 3. ANOVA results for the dependent variable THW.

Effect	df	F	p Value	$\eta_p{}^2$
MPR	3, 115,424	1776.439	<0.001	0.044
AV Behavior	1, 115,424	9.986	<0.001	<0.001
MPR*AV Behavior	3, 115,424	14.836	<0.050	<0.001

ANOVA was performed on Box–Cox transformed data (λ = −0.06); * represents the interaction among the variables.

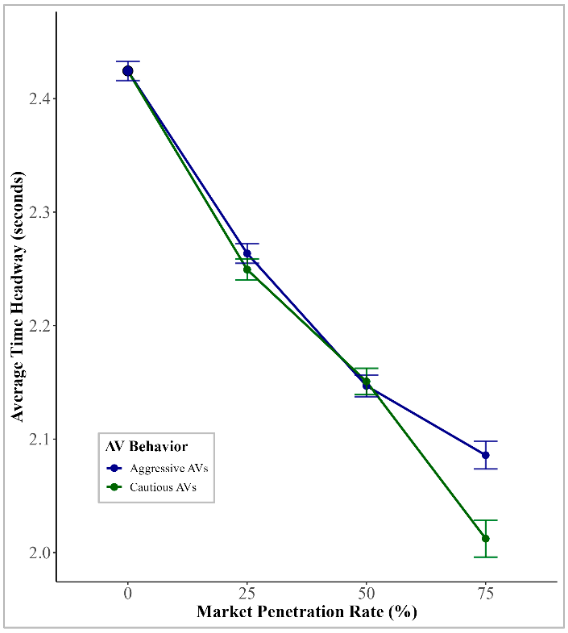

Figure 2. Effect of MPR and AV behavior on HDVs' THW.

Table 4. Tukey post hoc comparisons for the dependent variable THW.

Contrast	Mean Diff	95% CI	t Value	p Value	Cohen's d	95% CI d
MPR_0%–MPR_25% A	0.067	[0.059, 0.075]	25.924	<0.001	0.256	[0.237, 0.275]
MPR_0%–MPR_50% A	0.119	[0.110, 0.127]	42.068	<0.001	0.454	[0.433, 0.475]
MPR_0%–MPR_75% A	0.147	[0.137, 0.157]	43.254	<0.001	0.562	[0.536, 0.588]
MPR_25% A–MPR_50% A	0.052	[0.043, 0.061]	17.619	<0.001	0.198	[0.176, 0.220]
MPR_25% A–MPR_75% A	0.080	[0.069, 0.091]	22.902	<0.001	0.306	[0.280, 0.332]
MPR_50% A–MPR_75% A	0.028	[0.017, 0.039]	7.700	<0.001	0.108	[0.081, 0.136]
MPR_0%–MPR_25% C	0.073	[0.065, 0.081]	27.002	<0.001	0.280	[0.259, 0.300]
MPR_0%–MPR_50% C	0.117	[0.107, 0.126]	36.620	<0.001	0.447	[0.423, 0.471]
MPR_0%–MPR_75% C	0.182	[0.169, 0.195]	41.314	<0.001	0.696	[0.663, 0.730]
MPR_25% C–MPR_50% C	0.044	[0.033, 0.054]	12.911	<0.001	0.168	[0.142, 0.193]
MPR_25% C–MPR_75% C	0.109	[0.095, 0.123]	23.929	<0.001	0.417	[0.383, 0.451]
MPR_50% C–MPR_75% C	0.065	[0.050, 0.080]	13.416	<0.001	0.249	[0.213, 0.286]
MPR_25% A–MPR_25% C	0.006	[−0.002, 0.015]	2.176	>0.050	0.024	[0.002, 0.045]
MPR_50% A–MPR_50% C	−0.002	[−0.012, 0.009]	−0.505	>0.050	−0.007	[−0.033, 0.019]
MPR_75% A–MPR_75% C	0.035	[0.020, 0.050]	7.036	<0.001	0.134	[0.097, 0.172]

A: aggressive AVs; C: cautious AVs.

From a microsimulation perspective, at 75% MPR, the traffic flow is largely governed by the behavioral model of AVs. In the aggressive AVs scenario, these vehicles with smaller desired time headway limit the maneuverability for HDVs, resulting in HDVs' car-following model reacting by maintaining slightly larger THW. In contrast, in the cautious

AVs scenario, the availability of larger gaps created by AVs allow HDVs to follow them more closely and perform more lane changes. The differences in maneuverability to some extent explain the differences observed at 75% MPR of AVs. However, more investigations about the behavior of human drivers are required to confirm such a difference.

In general, these findings are consistent with the literature, reporting a smaller average time headway for human drivers when interacting with AVs at varying MPRs [30,31]. Additionally, studies focusing on individual interactions between AVs and HDVs have also reported a reduced average time headway for HDVs [24,25].

5.2. Effect of AVs on the Relative Velocity of HDVs

The results of analysis, as shown in Table 5, revealed a main effect of AVs' MPR on the RelVel of HDVs with a very small effect size [$F(3, 115{,}424) = 100.935$, $p < 0.001$, $\eta_p^2 = 0.003$]. In addition, a significant main effect of AV behavior [$F(1, 115{,}424) = 1615.139$, $p < 0.001$, $\eta_p^2 = 0.014$] and its interaction with AVs' MPR [$F(3, 115{,}424) = 589.452$, $p < 0.001$, $\eta_p^2 = 0.015$] on the RelVel of HDVs was present with small effect sizes.

Table 5. ANOVA results for the dependent variable RelVel.

Effect	df	F	*p* Value	η_p^2
MPR	3, 115,424	100.935	<0.001	0.003
AV Behavior	1, 115,424	1615.139	<0.001	0.014
MPR*AV Behavior	3, 115,424	589.452	<0.001	0.015

ANOVA was performed on Box–Cox transformed data (λ = 1.63); * represents the interaction among the variables.

As indicated in Figure 3, the changes in the RelVel of HDVs follow two different trends when interacting with aggressive and cautious AVs. The post hoc analyses showed that these visual differences are statistically significant at MPRs of 25% (mean difference = −7.771, $t = -18.789$, $p < 0.001$, d = −0.203), 50% (mean difference = −21.740, $t = -42.645$, $p < 0.001$, d = −0.568), and 75% (mean difference = −25.45, $t = -34.812$, $p < 0.001$, d = −0.665), with the effect sizes varying from small to moderate. Moreover, as the AVs' MPR increased, the reduction in the RelVel of HDVs during interactions with aggressive AVs was significant across all MPR levels, though with small effect sizes. In contrast, interactions with cautious AVs at an MPR of 25% did not significantly affect the RelVel of HDVs. However, at higher MPRs (50% and 75%), the increase in RelVel became significant but still associated with small effect sizes. Further details are provided in Table 6.

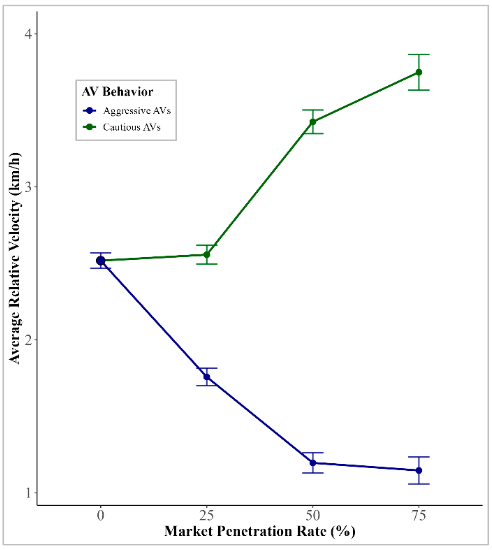

Figure 3. Effect of MPR and AV behavior on HDVs' RelVel.

Table 6. Tukey post hoc comparisons for the dependent variable RelVel.

Contrast	Mean. Diff	95% CI	*t* Value	*p* Value	Cohen's d	95% CI d
MPR_0%–MPR_25% A	7.392	[6.247, 8.538]	19.558	<0.001	0.193	[0.174, 0.213]
MPR_0%–MPR_50% A	12.793	[11.542,14.044]	30.990	<0.001	0.334	[0.313, 0.356]
MPR_0%–MPR_75% A	13.268	[11.761,14.775]	26.687	<0.001	0.347	[0.321, 0.372]
MPR_25% A–MPR_50% A	5.401	[4.099, 6.703]	12.574	<0.001	0.141	[0.119, 0.163]
MPR_25% A–MPR_75% A	5.876	[4.326, 7.425]	11.495	<0.001	0.154	[0.127, 0.180]
MPR_50% A–MPR_75% A	0.475	[−1.154, 2.104]	0.883	>0.050	0.012	[−0.015, 0.040]
MPR_0%–MPR_25% C	−0.379	[−1.580, 0.822]	−0.956	>0.050	−0.010	[−0.030, 0.010]
MPR_0%–MPR_50% C	−8.948	[−10.364, −7.532]	−19.153	<0.001	−0.234	[−0.258, −0.210]
MPR_0%–MPR_75% C	−12.18	[−14.14, −10.226]	−18.886	<0.001	−0.318	[−0.351, −0.285]
MPR_25% C–MPR_50% C	−8.570	[−10.074, −7.065]	−17.261	<0.001	−0.224	[−0.249, −0.199]
MPR_25% C–MPR_75% C	−11.80	[−13.823, −9.783]	−17.708	<0.050	−0.308	[−0.343, −0.274]
MPR_50% C–MPR_75% C	−3.233	[−5.388, −1.078]	−4.547	<0.001	−0.084	[−0.121, −0.048]
MPR_25% A–MPR_25% C	−7.771	[−9.025, −6.517]	−18.789	<0.001	−0.203	[−0.224, −0.182]
MPR_50% A–MPR_50% C	−21.74	[−23.29, −20.196]	−42.645	<0.001	−0.568	[−0.594, −0.542]
MPR_75% A–MPR_75% C	−25.45	[−27.67, −23.233]	−34.812	<0.001	−0.665	[−0.703, −0.628]

A: aggressive AVs; C: cautious AVs.

The observed decrease in the RelVel of HDVs when interacting with aggressive AVs aligns with the findings of de Zwart et al. [31], who found that human drivers' relative velocity decreases when interacting with aggressive AVs. This suggests that aggressive AVs' driving style may promote more harmonized driving behavior among human drivers. Conversely, the increase in the RelVel of HDVs in their interaction with cautious AVs may indicate an exploitation of the cautious behavior of AVs in practice, as found by Soni et al. [63]. In the context of simulation, the availability of larger gaps when interacting with cautious AVs provides more opportunities for lane changes. This, in turn, requires frequent speed adjustments relative to the leading vehicle, resulting in higher RelVel values for HDVs.

5.3. *Effect of AVs on the Acceleration and Deceleration Behavior of HDVs*

As indicated in Table 7, the results of ANOVA showed a significant main effect of MPR of AVs on the acceleration behavior of HDVs (Acc) with a small-to-medium effect size [$F(3, 115{,}424) = 1826.97$, $p < 0.001$, $\eta_p{}^2 = 0.045$]. There was also a significant main effect of AV behavior present, but with a very small effect size [$F(1, 115{,}424) = 296.520$, $p < 0.001$, $\eta_p{}^2 = 0.003$]. Additionally, the interaction between MPR and AV behavior was also significant [$F(3, 115{,}424) = 125.510$, $p < 0.001$, $\eta_p{}^2 = 0.003$], again with a very small effect size, suggesting that the effect of MPR on the acceleration of HDVs was only little affected by AV behavior. As shown in Figure 4, the increase in MPR of AVs, regardless of their driving styles, leads to a reduction in average acceleration of HDVs.

Table 7. ANOVA results for the dependent variable Acc.

Effect	df	F	*p* Value	$\eta_p{}^2$
MPR	3, 115,424	1826.970	<0.001	0.045
AV Behavior	1, 115,424	296.520	<0.001	0.003
MPR*AV Behavior	3, 115,424	125.510	<0.001	0.003

ANOVA was performed on Box–Cox transformed data (λ = 2.55); * represents the interaction among the variables.

However, the post hoc pairwise comparisons, as shown in Table 8, revealed that the magnitude of reduction in HDVs' average acceleration was different when interacting with aggressive and cautious AVs driving styles at MPRs of 25% (mean difference = 0.033, $t = 18.220$, $p < 0.001$, d = 0.20) and 50% (mean difference = 0.041, $t = 18.224$, $p < 0.001$, d = 0.24). However, the differences at an MPR of 75% were non-significant (mean difference = −0.010,

$t = -2.991$, $p > 0.050$, $d = -0.057$). This indicates that once reaching an MPR as high as 75%, the driving styles of AVs have no influence on the acceleration behavior of HDVs, likely due to the dominant presence of AVs creating a more homogeneous traffic flow where HDVs adapt to the prevailing AV driving patterns, irrespective of their driving styles. At lower MPRs of AVs, such as 25% and 50%, interaction with cautious AVs involves less acceleration by HDVs, because cautious AVs maintain larger headway distances, providing sufficient space for maneuvers. In contrast, aggressive AVs keep shorter gaps, requiring HDVs to accelerate more frequently to adjust to tighter traffic conditions. Furthermore, the results showed that with the increase in MPR of AVs, irrespective of their driving styles, a progressive larger difference in the average acceleration of HDVs was observed, ranging from a small-to-moderate effect size (Figure 4).

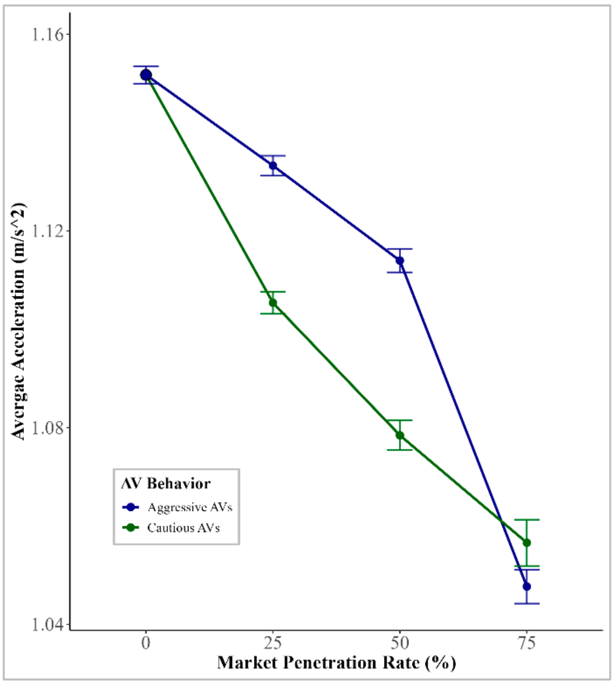

Figure 4. Effect of MPR and AV behavior on HDVs' acceleration.

Table 8. Tukey post hoc comparisons for the dependent variable Acc.

Contrast	Mean. Diff	95% CI	*t* Value	*p* Value	Cohen's d	95% CI d
MPR_0%–MPR_25% A	0.023	[0.018, 0.028]	13.617	<0.001	0.135	[0.115, 0.154]
MPR_0%–MPR_50% A	0.046	[0.040, 0.051]	25.182	<0.001	0.272	[0.251, 0.293]
MPR_0%–MPR_75% A	0.121	[0.114, 0.127]	55.026	<0.001	0.715	[0.689, 0.741]
MPR_25% A–MPR_50% A	0.023	[0.017, 0.029]	12.220	<0.001	0.137	[0.115, 0.159]
MPR_25% A–MPR_75% A	0.098	[0.091, 0.105]	43.453	<0.001	0.580	[0.554, 0.607]
MPR_50% A–MPR_75% A	0.075	[0.068, 0.082]	31.561	<0.001	0.443	[0.416, 0.471]
MPR_0%–MPR_25% C	0.056	[0.051, 0.061]	32.010	<0.001	0.331	[0.311, 0.352]
MPR_0%–MPR_50% C	0.087	[0.081, 0.093]	42.138	<0.001	0.515	[0.491, 0.539]
MPR_0%–MPR_75% C	0.111	[0.102, 0.120]	39.023	<0.001	0.658	[0.625, 0.691]
MPR_25% C–MPR_50% C	0.031	[0.024, 0.038]	14.107	<0.001	0.183	[0.158, 0.208]
MPR_25% C–MPR_75% C	0.055	[0.046, 0.064]	18.735	<0.001	0.326	[0.292, 0.361]
MPR_50% C–MPR_75% C	0.024	[0.015, 0.034]	7.7120	<0.001	0.143	[0.107, 0.180]
MPR_25% A–MPR_25% C	0.033	[0.028, 0.039]	18.220	<0.001	0.197	[0.176, 0.218]
MPR_50% A–MPR_50% C	0.041	[0.034, 0.048]	18.224	<0.001	0.243	[0.217, 0.269]
MPR_75% A–MPR_75% C	−0.010	[−0.019, 0.00]	−2.991	>0.050	−0.057	[−0.095, −0.02]

A: aggressive AVs; C: cautious AVs.

Regarding the deceleration of HDVs, as shown in Table 9, the results of ANOVA showed a significant main effect of MPR of AVs on the deceleration behavior of HDVs (Dec) with a large effect size [$F(3, 115{,}424) = 4684.939$, $p < 0.001$, $\eta_p^2 = 0.109$]. There was also a significant main effect of AV behavior with a small effect size present [$F(1, 115{,}424) = 486.316$, $p < 0.001$, $\eta_p^2 = 0.017$] on the deceleration behavior of HDVs. Additionally, the interaction between MPR and AV behavior was also significant [$F(3, 115{,}424) = 1947.696$, $p < 0.001$, $\eta_p^2 = 0.012$], indicating that the impact of MPR on the deceleration of HDVs varied depending on AV behavior. As shown in Figure 5, the increase in the MPR of AVs leads to a reduction in the magnitude of deceleration of HDVs, regardless of the driving styles of AVs.

Table 9. ANOVA results for the dependent variable Dec.

Effect	df	F	*p* Value	η_p^2
MPR	3, 115,424	4684.939	<0.001	0.109
AV Behavior	1, 115,424	486.316	<0.001	0.017
MPR*AV Behavior	3, 115,424	1947.696	<0.001	0.012

ANOVA was performed on Box–Cox transformed data (λ = 1.37) after shifting all values by ∣min(Dec)∣ + 0.001 to accommodate non-positive values; * represents the interaction among the variables.

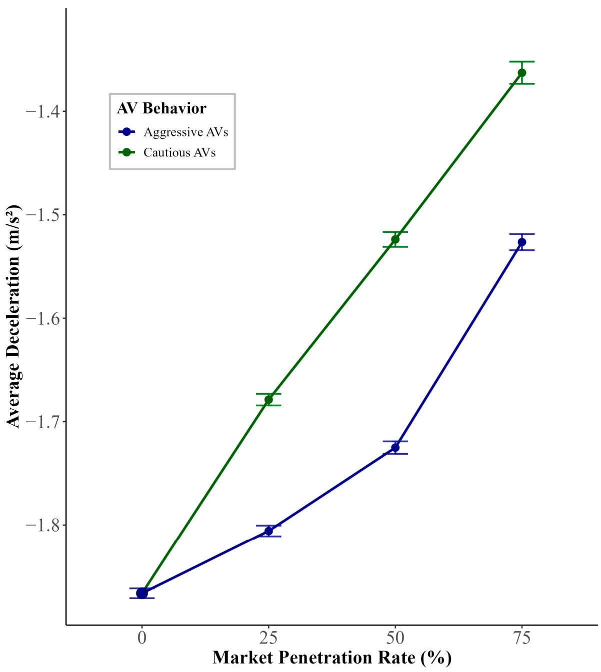

Figure 5. Effect of MPR and AV behavior on HDVs' deceleration.

The results of pairwise comparisons, as shown in Table 10, indicated that AVs' driving styles differently influenced the decrease in HDVs' average deceleration (when expressed in absolute values). There were significant differences between the aggressive and cautious AVs driving styles at the MPRs of 25% with a small-to-moderate effect size (mean difference = −0.232, $t = -32.458$, $p < 0.001$, d = −0.351), 50% with a moderate-to-large effect size (mean difference = −0.370, $t = -42.065$, $p < 0.001$, d = −0.561), and 75% with small-to-moderate effect size (mean difference = −0.305, $t = -24.158$, $p < 0.001$, d = −0.462). Moreover, the post hoc analysis showed that with the increasing AVs' MPR, the average deceleration of HDVs decreased in absolute terms when interacting with aggressive AVs, exhibiting effect sizes ranging from small to large. In contrast, interactions with cautious AVs resulted in moderate-to-large effect sizes.

Table 10. Tukey post hoc comparisons for the dependent variable Dec.

Contrast	Mean. Diff	95% CI	*t* Value	*p* Value	Cohen's d	95% CI d
MPR_0%–MPR_25% A	−0.109	[−0.129, −0.090]	−16.752	<0.001	−0.165	[−0.185, −0.146]
MPR_0%–MPR_50% A	−0.256	[−0.278, −0.235]	−35.947	<0.001	−0.388	[−0.409, −0.367]
MPR_0%–MPR_75% A	−0.621	[−0.647, −0.595]	−72.418	<0.001	−0.941	[−0.967, −0.915]
MPR_25% A–MPR_50% A	−0.147	[−0.169, −0.124]	−19.807	<0.001	−0.222	[−0.244, −0.200]
MPR_25% A–MPR_75% A	−0.512	[−0.539, −0.485]	−58.052	<0.001	−0.776	[−0.802, −0.749]
MPR_50% A–MPR_75% A	−0.365	[−0.393, −0.337]	−39.382	<0.001	−0.553	[−0.581, −0.526]
MPR_0%–MPR_25% C	−0.341	[−0.362, −0.320]	−49.863	<0.001	−0.516	[−0.537, −0.496]
MPR_0%–MPR_50% C	−0.626	[−0.651, −0.602]	−77.665	<0.001	−0.948	[−0.973, −0.924]
MPR_0%–MPR_75% C	−0.926	[−0.960, −0.892]	−83.200	<0.001	−1.403	[−1.436, −1.369]
MPR_25% C–MPR_50% C	−0.285	[−0.311, −0.259]	−33.292	<0.001	−0.432	[−0.457, −0.406]
MPR_25% C–MPR_75% C	−0.585	[−0.620, −0.550]	−50.874	<0.001	−0.886	[−0.921, −0.852]
MPR_50% C–MPR_75% C	−0.300	[−0.337, −0.263]	−24.444	<0.001	−0.454	[−0.491, −0.418]
MPR_25% A–MPR_25% C	−0.232	[−0.253, −0.210]	−32.458	<0.001	−0.351	[−0.372, −0.330]
MPR_50% A–MPR_50% C	−0.370	[−0.397, −0.343]	−42.065	<0.001	−0.561	[−0.587, −0.534]
MPR_75% A–MPR_75% C	−0.305	[−0.343, −0.267]	−24.158	<0.001	−0.462	[−0.499, −0.424]

A: aggressive AVs; C: cautious AVs.

Similar to the acceleration behavior, with the increasing AVs' MPR, the magnitude of deceleration in HDVs decreases, and this is more evident when dealing with cautious AVs, because their predictable and conservative driving style minimizes sudden braking events, allowing HDVs to adjust speed gradually and maintain smoother deceleration profiles. These findings match of those in the literature, reporting the improvement of human drivers' acceleration and deceleration behaviors in the interaction with AVs [24–26]. The improvement in acceleration and deceleration behavior of vehicles is often linked with better traffic stability [64] and fuel consumption and vehicle emissions [65]. The positive effect of AVs on the behavior of HDVs in terms of the average acceleration and deceleration indicates that the deterministic driving behavior of AVs promotes smoother interactions, reducing the need for abrupt speed changes by human drivers. This consistency allows HDVs to anticipate surrounding vehicle movements more accurately, leading to steadier acceleration/deceleration patterns and enhanced traffic stability.

5.4. Effect of AVs on the Frequency of Lane Change in HDVs

Statistical analysis showed that AVs' MPR had a significant effect on the lane change frequency of HDVs with a medium-to-large effect size [$F(3, 115{,}424) = 4177.593$, $p < 0.001$, $\eta_p{}^2 = 0.098$]. A significant main effect of AV behavior with a large effect size [$F(1, 115{,}424) = 18{,}316.535$, $p < 0.001$, $\eta_p{}^2 = 0.137$] and the interaction effect of MPR and AV behavior with a medium-to-large effect size [$F(3, 115{,}424) = 5663.996$, $p < 0.001$, $\eta_p{}^2 = 0.128$] existed. This suggests that the impact of AVs' MPR on the LnCh varies depending on the driving styles of AVs. Table 11 presents the result of the two-way ANOVA for the dependent variable LnCh.

Table 11. ANOVA results for the dependent variable LnCh.

Effect	df	F	*p* Value	$\eta_p{}^2$
MPR	3, 115,424	4177.593	<0.001	0.098
AV Behavior	1, 115,424	18,316.535	<0.001	0.137
MPR*AV Behavior	3, 115,424	5663.996	<0.001	0.128

ANOVA was performed on Box–Cox transformed data (λ = 0.79) after shifting all values by |min(LnCh)| + 0.001 to accommodate non-positive values; * represents the interaction among the variables.

As indicated in Figure 6, as the AVs' MPR increases, HDVs make more lane changes when interacting with cautious AVs but fewer when interacting with aggressive AVs. These different trends are statistically significant between aggressive and cautious AVs' driving styles at MPRs of 25% (mean difference = −3.441, t = −80.525, p < 0.001, d = −0.870), 50% (mean difference = −6.382, t = −121.158, p < 0.001, d = −1.614), and 75% (mean difference = −8.983, t = −118.933, p < 0.001, d = −2.272), with large effect sizes at all MPRs. The reduced number of lane changes in HDVs in the interaction with aggressive AVs indicates that the shorter gaps discourage HDVs from frequently changing lanes, as opportunities for safe lane changes are limited. In contrast, the interaction with cautious AVs, which is associated with a higher number of lane changes, is likely due to the larger gaps and more accommodating driving behavior of these vehicles, providing HDVs with more opportunities to execute lane changes. Table 12 provides further details about the pairwise comparison.

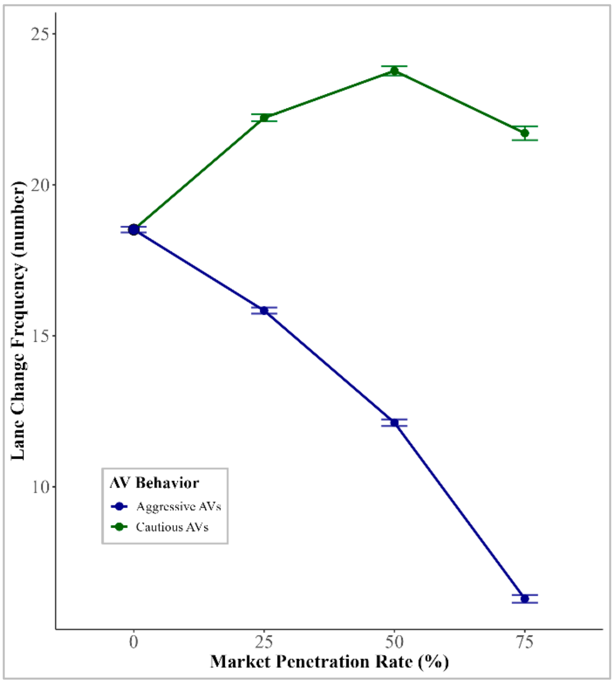

Figure 6. Effect of MPR and AV behavior on HDV LnCh.

Table 12. Tukey post hoc comparisons for the dependent variable lane change frequency (LnCh).

Contrast	Mean. Diff	95% CI	t Value	p Value	Cohen's d	95% CI d
MPR_0%–MPR_25% A	1.476	[1.357, 1.594]	37.789	<0.001	0.373	[0.354, 0.393]
MPR_0%–MPR_50% A	3.610	[3.481, 3.739]	84.642	<0.001	0.913	[0.892, 0.935]
MPR_0%–MPR_75% A	7.283	[7.127, 7.438]	141.775	<0.001	1.842	[1.816, 1.869]
MPR_25% A–MPR_50% A	2.134	[2.000, 2.269]	48.095	<0.001	0.540	[0.518, 0.562]
MPR_25% A–MPR_75% A	5.807	[5.647, 5.967]	109.957	<0.001	1.469	[1.442, 1.496]
MPR_50% A–MPR_75% A	3.672	[3.504, 3.841]	66.139	<0.001	0.929	[0.901, 0.957]
MPR_0%–MPR_25% C	−1.965	[−2.089, −1.841]	−48.010	<0.001	−0.497	[−0.518, −0.477]
MPR_0%–MPR_50% C	−2.772	[−2.918, −2.626]	−57.422	<0.001	−0.701	[−0.725, −0.677]
MPR_0%–MPR_75% C	−1.701	[−1.903, −1.499]	−25.520	<0.001	−0.430	[−0.463, −0.397]
MPR_25% C–MPR_50% C	−0.806	[−0.962, −0.651]	−15.722	<0.001	−0.204	[−0.229, −0.179]
MPR_25% C–MPR_75% C	0.265	[0.056, 0.473]	3.843	<0.050	0.067	[0.033, 0.101]
MPR_50% C–MPR_75% C	1.071	[0.848, 1.294]	14.580	<0.001	0.271	[0.235, 0.307]
MPR_25% A–MPR_25% C	−3.441	[−3.571, −3.312]	−80.525	<0.001	−0.870	[−0.892, −0.849]
MPR_50% A–MPR_50% C	−6.382	[−6.542, −6.222]	−121.158	<0.001	−1.614	[−1.641, −1.587]
MPR_75% A–MPR_75% C	−8.983	[−9.212, −8.754]	−118.933	<0.001	−2.272	[−2.311, −2.234]

A: aggressive AVs; C: cautious AVs.

6. Conclusions

The study examined the behavioral adaptation of HDVs induced by AVs with aggressive and cautious driving styles at varying MPRs, ranging from 0% to 75% in 25% increments. Using driving simulator data enabled us to calibrate all behavioral parameters for HDVs and to build the baseline scenario in VISSIM. The behavior of AVs was modeled by considering their practical capabilities. The results indicated that HDVs adapt their driving behavior when interacting with AVs in the microsimulation context, and this adaptation varies in certain aspects depending on the AVs' driving styles. More specifically, the study concludes the following:

- Average time headway of HDVs decreases as the MPR of AVs increases with a small-to-medium effect size. The cautious driving styles of AVs lead to a higher reduction in HDVs' average time headway at an MPR of 75% as compared with aggressive AVs (supporting H1);
- The relative speed of HDVs changes during interactions with AVs as the MPR of AVs increases with a very small effect size. It increases when interacting with cautious AVs, while decreasing when dealing with aggressive AVs (rejecting H2);
- The average acceleration of HDVs decreases when interacting with an increasing rate of AVs with a small-to-medium effect size; the driving styles of AVs did not influence the reduction in average acceleration (partially supporting H3), and their average deceleration also decreases in absolute terms with a large effect size. it reduces more when interacting with cautious AVs as compared with aggressive AVs (supporting H4);
- An increase in the MPR of AVs influences the frequency of lane changes in HDVs with a medium-to-large effect size. However, this effect depends on the AVs' driving styles, with aggressive AVs leading to fewer lane changes in HDVs, while interaction with cautious AVs results in more frequent lane changes (rejecting H5);

Overall, the results suggest that AVs induce HDVs to adapt their driving behavior in the microsimulation context, which may serve as an indicator of the evolving nature of future traffic conditions. Among the behavioral indicators examined in this study, an increase in the MPR of AVs significantly influenced HDV behavior in terms of average deceleration and frequency of lane changes, with large effect sizes, highlighting that AVs have the highest impacts on the deceleration and the number of lane changes in HDVs. Specifically, HDVs adapted their driving behavior by braking less sharply and performing more lane changes when interacting with cautious AVs but fewer lane changes when interacting with aggressive AVs.

Additionally, the presence of AVs, regardless of driving style, affected HDVs' average time headway and average acceleration, though with small-to-medium effect sizes, suggesting more modest impacts of AVs on spacing and acceleration behavior of HDVs. In contrast, HDVs' relative velocity was minimally influenced by increasing AV penetration rates, indicating that AVs influence the relative velocity of HDVs with a minimal real-world effect. However, the findings of this study are subject to certain limitations, including the omission of intentional behavior changes among human drivers influenced by their trust and emotions toward AVs. Further studies involving human drivers, such as human-in-the-loop experiments, are needed to observe these behavioral dynamics more comprehensively. In addition, the results of the present study indicate the behavioral adaptation of HDVs induced by the increasing presence of AVs in a virtual setting. While these results provide useful insights into the dynamics of the mixed traffic flow of AVs and HDVs, real-world human driving behavior in the mixed traffic flow remains to be validated in future studies. Furthermore, the findings are limited to the highway context; in urban settings, the effects of AVs on the behavior of HDVs may differ due to variations in traffic characteristics, such as speed limits and stop-and-go conditions. Thus, the investigation of AV effects on the behavior of HDVs in urban context remains a topic for future research. Also, in the present study, we examined the effects of cautious and aggressive AV driving styles on the behavior of HDVs. However, other driving styles, such as intermediate or adaptive styles, as well as mixed driving styles for AVs, may influence HDV behavior differently and are directions for future research.

Author Contributions: Conceptualization: M.S., M.G. and R.R.; methodology: M.S., R.C., F.O., M.G. and R.R.; software: M.S., R.C. and F.O.; validation: M.S., R.C. and F.O.; formal analysis: M.S., R.C., and F.O.; investigation: M.S.; data curation: R.C. and M.S.; writing—original draft: M.S.; writing—review and editing: R.C., F.O., R.R. and M.G.; visualization: M.S.; supervision: M.G. and R.R.; funding acquisition: F.O., R.R. and R.C. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: The driving simulator experiment procedure received approval from the Ethics Committee of the Human Inspired Technology (HIT) Research Centre at the University of Padova (ID: 2023_223R3) on 1 February 2024, according to the code of Ethics of the World Medical Association.

Informed Consent Statement: All the participants of the driving simulator experiment provided their consent in a written format.

Data Availability Statement: Data available on request due to restrictions (e.g., privacy, legal, or ethical reasons).

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