The Open Transportation Journal
DOI: 10.2174/0126671212453946260129104511, 2026, 20, e26671212453946
ISSN: 1874-4478


RESEARCH ARTICLE OPEN ACCESS

# Comparative Analysis of Fixed and Dynamic Adaptive Cruise Control Settings for Automated Vehicles using Microsimulation

Masoud Saljoqi[1], Riccardo Ceccato[1,*], Gregorio Gecchele[1,3], Riccardo Rossi[1] and Massimiliano Gastaldi[1,2]

[1]ICEA, University of Padova, Padua, Italy
[2]Department of General Psychology, University of Padova, via Venezia, 8, 3313, Padua, Italy
[3]Atraki s.r.l, via A. Diaz, 4, Sant'Ambrogio di Valpolicella, 37015, Verona, Padua, Italy

**Abstract:**

***Introduction:*** Partially Automated Vehicles (AVs) with Adaptive Cruise Control (ACC) have been introduced, and their impacts have mainly been studied through microsimulation. Most research varies ACC headway settings to represent driving styles but assumes they remain constant. In reality, drivers often adjust headway due to traffic conditions. This study examines how such dynamic behavior affects traffic efficiency compared to a fixed ACC setting on a highway in Veneto, Italy.

***Methods:*** Microsimulation analyses were performed in VISSIM software, considering average travel time, average speed, and flow rate as traffic performance metrics across varying Market Penetration Rates (MPRs) of AVs, ranging from 0% to 100% in a step of 25%. ANOVA was used for statistical testing.

***Results:*** The results indicated that with an increase in MPRs of AVs, travel time increases, while speed and flow rate reduce. Dynamically changing the headway settings for ACC further worsens traffic performance metrics, where travel time increases by about 55%, speed and flow rate reduce by about 30% and 25%, respectively.

***Discussion:*** These results highlight the importance of incorporating realistic drivers' preferences in ACC modeling, as neglecting the dynamic nature of headway preferences in ACC users may lead to overly optimistic evaluations of AV impacts on traffic efficiency.

***Conclusion:*** In this study, traffic performance declined as AV penetration increased, and the effects were stronger when drivers adjusted headway dynamically rather than keeping it fixed. These outcomes emphasize the need to reflect realistic driving behavior in ACC modeling to generate more reliable expectations for future traffic operations.

**Keywords:** Traffic efficiency, Automated vehicles, Adaptive cruise control, Mixed traffic flow, VISSIM, Microsimulation analysis, Smart mobility.



*Address correspondence to this author at the ICEA, University of Padova, Padua, Italy; E-mail: riccardo.ceccato@unipd.it

*Cite as:* Saljoqi M, Ceccato R, Gecchele G, Rossi R, Gastaldi M. Comparative Analysis of Fixed and Dynamic Adaptive Cruise Control Settings for Automated Vehicles using Microsimulation. Open Transp J, 2026; 20: e26671212453946.
http://dx.doi.org/10.2174/0126671212453946260129104511

Received: November 06, 2025
Revised: December 03, 2025
Accepted: December 12, 2025
Published: February 25, 2026



## 1. INTRODUCTION

The transportation industry has entered a new era with the introduction of Automated Vehicles (AVs), which are expected to transform current traffic patterns into a safer and more efficient system [1-5]. However, the replacement of conventional vehicles with these technologies will be somewhat of a prolonged process due to the infrastructure and technological requirements for the large-scale deployment of AVs [6, 7]. Therefore, a relatively long period, known as the transition phase, is anticipated during which Human-Driven Vehicles (HDVs) will coexist with AVs on roadways.

Considering the performance and driving tasks of AVs, the Society of Automotive Engineers (SAE) has categorized them into six different categories, ranging from Level 0 to Level 5. AVs with levels up to 3 have driver assistance features, while higher levels of AVs (*i.e.*, Levels 4 and 5) are equipped with automated driving functionalities [5, 8]. Although the introduction of highly automated AVs requires infrastructural and technical requirements, Level 2 AVs are widely available in the market, and Level 3 AVs have passed legal requirements in a few countries [5]. The availability of Level 2 AVs enables the assessment of their effectiveness in improving traffic efficiency during the transition phase, offering valuable insights into future traffic conditions. These vehicles are equipped with Adaptive Cruise Control (ACC) that allows users to select a headway setting among a range of available options through driving [9, 10].

The effects of AVs on traffic efficiency have been studied mostly using the microsimulation method in the absence of real-world data on HDV-AV interactions during the transition phase. The behavior of AVs has been programmed through adjusting behavioral parameters in a virtual environment, mostly by modifying the time headway parameter that mimics the ACC controller in AVs. To evaluate the influence of AVs on traffic efficiency, the Market Penetration Rate (MPR) of AVs has been gradually increased, and traffic performance metrics have been accordingly evaluated. Since these vehicle types have different driving styles due to the differences in users' preferences or manufacturing [11, 12], the time headway parameter has been adjusted in the microsimulation studies to account for the variability in the driving styles of AVs. As a common practice, a larger headway setting has been assigned to AVs to simulate the behavior of AVs up to Level 3, while higher level AVs have been simulated with a smaller headway, representing the cooperation capabilities of AVs.

Previous studies focusing on the introduction of AVs with cooperation capabilities have extensively reported the positive impacts of these vehicle types on traffic efficiency. Aria *et al*. [13] simulated AVs with cooperative capabilities, reporting a 9% decrease in average travel time with the increase in AVs' MPR. Szimba and Hartmann [14] revealed that Level 5 and Level 4 AVs decrease travel time by 27% and 20%, respectively. Similarly, Rahman *et al.* [15], who studied the effects of AVs on travel time, found that AVs with cooperative capabilities reduce travel time compared to those lacking such functionalities and decrease crash risk. Spiliopoulou *et al.* [16] studied the effects of AVs on capacity and delay, indicating that the increase in MPR of AVs, irrespective of their driving styles, leads to a reduction in delay, while low-level AVs negatively affect capacity. The findings of a study by Rezaei and Caulfield [17] confirmed the decrease in delay with the increase in the presence of AVs and indicated that the maximum gains in delay will be achieved at an AV MPR as large as 60%. The increase in MPR of AVs was shown to decrease delay by up to 31% [18], and AV MPRs higher than 50% improve traffic stability [19]. In line with these findings, Beza *et al.* [20] found that the increase in MPR of AVs leads to a reduction in travel time and delay. Overall, studies simulating AVs with a time headway below 1.2 seconds found significant improvements in traffic efficiency with the introduction of AVs. This has also been found in one of the earliest studies by Minderhoud and Bovy [21], who indicated that AVs with a time headway of 1.2 seconds or higher do not increase capacity.

However, studies focusing on the effects of low-level AVs (*i.e.*, up to Level 3) have reported contrasting results. For example, Sekar *et al*. [22] simulated AVs with varying driving styles by assigning various headway settings to AVs and found that the increase in MPR of AVs, regardless of their driving styles, decreases travel time; however, Lu *et al*. [23] found that only the aggressive driving style of AVs contributes to a shorter travel time and higher speeds. These dissimilarities in the findings are essentially due to different assumptions about the behavior of AVs. Shang and Stern [24] investigated the effects of AVs based on their theoretical and practical capabilities and found that theoretical AVs improve capacity by up to 7%, while commercially available AVs decrease capacity by up to 35%. Focusing on the practical capabilities of AVs, Saljoqi *et al.* [25] studied the effects of Level 2 AVs with different driving styles based on the users' preferences and found that travel time and delay increase with the rise in MPR of AVs, and only aggressive AVs, with a smaller time headway compared to HDVs, can improve traffic efficiency. Mattas *et al.* [26] have emphasized that the effects of AVs on traffic efficiency largely depend on their desired time headway, with a larger time headway resulting in a reduction in average speed at the network level.

As reported in prior studies, the desired time headway in AVs is a critical factor influencing their effects on traffic efficiency. For low-level AVs, such as Level 2, the desired headway setting for ACC is primarily determined by users and may vary according to their personal preferences. Consequently, assigning a single driving style to AVs may not be an effective approach, as the preferences of AVs' users vary depending on their own driving style, with drivers preferring a driving style for AVs that matches their own or is more defensive [11, 12]. As a common approach, most previous studies assigned one specific driving style to AVs to assess their impacts, with the exception of Saljoqi *et al.* [25], who defined the driving styles of AVs based on the observed driving behavior of their users across varying AV MPRs with different proportions.

In addition, studies have shown that drivers' driving style is not fixed and may vary depending on external factors such as environmental and traffic conditions [27-29]. Lei *et al.* [27] indicated that while a driver's overall driving style may remain the same during their entire career, it can change during individual journeys due to factors such as traffic conditions, driving tasks, and other factors, a phenomenon termed "staged changes" in the driving style. This suggests that drivers' use of headway settings for ACC in AVs may also be dynamic rather than fixed, responding to varying traffic conditions. Pereira *et al*. [30] showed that headway settings used for ACC vary depending on the traffic environment: in urban settings, often associated with lower speed and higher density, drivers tend to select shorter headways compared to motorway environments.

Prior studies on AVs have examined their influence on traffic efficiency through microsimulation, often focusing on the impact of AV cooperation capabilities. High-level or cooperative AVs consistently improved travel time, delay, and traffic stability [13-21]. In contrast, studies on low-level AVs (up to Level 3) reported mixed results: some showed performance gains regardless of driving style [22], while others indicated that only aggressive AVs or those with smaller headway achieve improved traffic outcomes [23-26]. Additionally, existing studies highlight the importance of headway selection in determining traffic outcomes; however, most microsimulation research assumes that AVs operate with a fixed ACC headway setting. Although some work has examined variation in AV driving styles, it has not addressed how drivers may override and dynamically adjust ACC headway in response to changing traffic or environmental conditions. Consequently, the combined effects of driving-style heterogeneity and short-term dynamic headway selection behavior of ACC users remain insufficiently explored. This study aims to fill this gap by incorporating both aspects within a single microsimulation framework.

## 2. OBJECTIVES AND CONTRIBUTIONS

The study aimed to investigate the effects of Level 2 AVs on traffic efficiency, as measured by average travel time, average speed, and flow rate, during the transition phase at varying AV MPRs. Specifically, the present study offers the following contributions to existing literature:

- Assigning a mix of different driving styles (cautious, normal, and aggressive) to AVs, considering their users' observed driving styles.
- Considering the dynamic behavior of users in selecting ACC headway settings during driving, representing the short-term driving style of human drivers.

The research meant answering the following research questions:

RQ1: Does increasing the MPR of Level 2 AVs influence traffic efficiency on highways?

RQ2: To what extent does considering the dynamic behavior of ACC users in selecting headway settings influence traffic efficiency?

Based on the findings of previous studies and our assumptions, the following hypotheses are presented:

- $H_1$—$H_3$: Increasing the MPR of Level 2 AVs improves traffic efficiency by decreasing average travel time ($H_1$), while increasing average speed ($H_2$) and flow rate ($H_3$).
- $H_4$—$H_6$: The impact of the dynamic *versus* fixed driving behavior of AV users in setting headway for ACC significantly varies with respect to average travel time ($H_4$), average speed ($H_5$), and flow rate ($H_6$) across different MPRs of AVs.

## 3. MATERIALS AND METHODS

A microsimulation method was used to fulfill the objectives of the study. VISSIM, a frequently adopted and powerful microsimulation tool for analyzing the mixed traffic flow involving AVs and HDVs [20], was used to examine the effects of AVs with different driving styles on traffic efficiency under various scenarios. Traffic efficiency metrics were evaluated at five AV MPRs (0%, 25%, 50%, 75%, and 100%). The AV MPR of 0% (no AVs) served as the baseline scenario against which the results of other scenarios were compared.

### 3.1. Study Area and Data Description

Traffic data were collected using two complementary sources. First, floating car data were gathered along the 15 km highway segment during the reference period to obtain real travel times for calibration. Second, traffic counters recorded flow data for Heavy Goods Vehicles (HGVs), Light Goods Vehicles (LGVs), and Passenger Vehicles (PVs) during peak hours (07:45–09:15 AM) on a working day. For the clustering and calibration phases, approximately 22,500 vehicle observations were used, ensuring a robust sample for capturing traffic variability across vehicle types and time intervals. The first and last 15 minutes of traffic data were used as warm-up and cool-down periods. Average travel times from the simulation outputs, calculated over the middle 12 km of the segment (excluding the first and last 1.5 km to avoid start-up and end-of-simulation effects), were compared against the real travel times derived from floating car data to validate the baseline scenario.

### 3.2. Driver Driving Style Classification

The K-means algorithm, a commonly used non-hierarchical clustering method for metric data [31], was employed to classify the driving styles of drivers into three categories: cautious, normal, and aggressive, based on their observed time headway. To validate the three-cluster solution, the average silhouette width, which was 0.6, indicating a reasonable separation between clusters, was calculated. Additionally, the ratio of the average squared distance between cluster centroids to the sum of squared distances within clusters was 0.89, further confirming the suitability of the three-cluster partition. This approach also allowed for determining the proportion of each driving style category. Table **1** shows the proportion of each driving style along with the average time headway for each driving class [25].

To avoid ambiguity, it is important to clarify how ACC behavior was conceptualized in this study. ACC, in this context, refers to the car-following system used by Level 2 AVs, where the following distance is regulated using an adjustable time headway setting. Dynamic ACC refers to a behavioral mode in which the time headway setting is not fixed but may change during the trip depending on users' perceived driving conditions. In contrast, Fixed ACC represents the conventional implementation of ACC in modeling, where the selected headway remains constant throughout the trip. Under this scenario, each driver uses only the baseline (normal) headway for that class with no adjustment triggered by traffic or environmental conditions.

**Table 1. The proportion of driving styles and their average time headway.**

| Driving Style | Average Time Headway (Seconds) | Standard Deviation (Seconds) | The Proportion |
|---|---|---|---|
| Aggressive | 0.70 | 0.32 | 46% |
| Normal | 1.87 | 0.36 | 31% |
| Cautious | 3.20 | 0.70 | 23% |

To analyze the dynamic behavior of ACC users in selecting time headway settings, three options were defined based on the average time headway provided in Table **1** and were applied under different hypothetical traffic conditions. The selected ACC headway settings were based on the closest similar option to the observed average time headway for each driving style group or more defensive available headway options in Level 2 AVs, within a range of 0.5 seconds. This assumption was made because previous studies have shown that ACC users prefer driving styles similar to their own or slightly more defensive for AVs [11, 12]. Table **2** presents these headway options, which were used in the simulation.

**Table 2. ACC headway options used in the simulation.**

| Driving Style | Option 1 (Normal) | Option 2 (Aggressive) | Option 3 (Cautious) |
|---|---|---|---|
| Aggressive | 1 s | 1 s | 1.5 s |
| Normal | 2 s | 1.5 s | 2.5 s |
| Cautious | 3 s | 2.5 s | 4.0 s |

Option 1 shows the baseline time headway normally used by ACC users. It was defined based on the observed average time headway for each driving style and matched the closest available headway settings for ACC in commercially available Level 2 AVs. Option 2 represents a more aggressive headway setting, calculated as the observed average time headway minus one standard deviation for each driving style, and this value matched the closest available headway settings for ACC or a slightly more defensive option. ACC users may shift to this setting in free-flow conditions, when they are in a hurry, or when they have a high level of trust in the AV system. Option 3 indicates a more cautious time headway setting, calculated as the observed average time headway plus one standard deviation for each driving style, and it matched the closest available headway setting in Level 2 AVs. This setting was defined for the conditions where ACC users may adopt a slightly more cautious headway setting, such as under poor visibility, stop-and-go traffic, or congested traffic situations, primarily due to safety concerns. As shown in Fig. (**1**), the logic for triggering transitions is as follows: ACC users may shift from Option 1 to Option 2 in free-flow conditions, when they are in a hurry, or when they have a high level of trust in the AV system. Conversely, Option 3 is adopted under more cautious scenarios, such as poor visibility or stop-and-go traffic, primarily due to safety considerations. It should be noted that these conditions are hypothetical and were assumed to represent plausible short-term behavioral adjustments of ACC users during a trip. The ±1 standard deviation was assumed to capture realistic short-term behavioral variations in ACC users without causing radical changes in their headway preferences, as larger deviations could even shift drivers into a different driving style, which would not be a solid assumption. It is worth noting that the minimum headway setting for Option 2 was not set below 1 second, as it aligns with the lowest available ACC headway setting reported in the manuals of many commercially available AVs [8].

### 3.3. Simulation Environment and Setup

The highway segment used for data collection was replicated in VISSIM (25.00, *SP07*). The middle 12 km section was divided into three equal-length subsegments, where the dynamic ACC scenario was tested. Fig. (**1**) illustrates the highway segments and the conditions under which the dynamic behavior of ACC users was simulated.

Two simulation scenarios were examined in the present study. In the first scenario, the behavior of ACC users was assumed to be dynamic, varying in response to users' perceptions of traffic and other influencing factors. Changes in the time headway setting under this scenario are indicated in Fig. (**1**). The second scenario involved the commonly used approach, in which the headway-setting behavior of ACC users was assumed to be fixed, with the ACC headway setting set to the normally used option and remaining unchanged throughout the trip. For both scenarios, the MPR of AVs was increased from 0% to 100% in 25% increments, with the percentage of each driving style modified accordingly. Table **3** presents the shares of each driving style at different AV MPRs.

**Table 3. The proportion of each driving style at varying AV MPRs.**

| Driving Style | Share of AV Driving Style at MPRs | | | | |
|---|---|---|---|---|---|
| | 0% | 25% | 50% | 75% | 100% |
| Aggressive | - | 11.5 | 23 | 34.5 | 46 |
| Normal | - | 7.75 | 15.5 | 23.25 | 31 |
| Cautious | - | 5.75 | 11.5 | 17.25 | 23 |

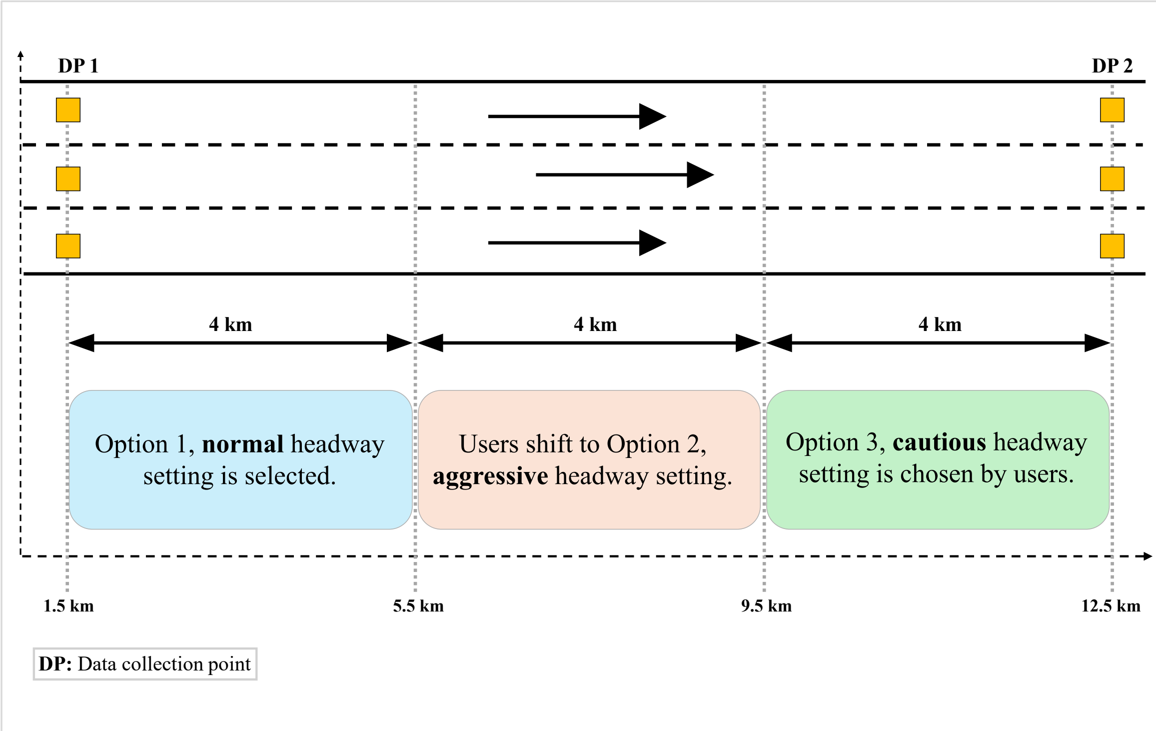


**Fig. (1).** Simulation environment.

The baseline scenario (MPR = 0%) was calibrated utilizing the observed data, a crucial step to ensure the model's realism [32]. The behavior of HDVs was modeled using the Weidemann 99 car-following model available in VISSIM. This psychophysical model regulates a vehicle's speeding and spacing behavior based on its driver's perception thresholds. A detailed description of this model is provided by Aghabayk *et al.* [33]. The behavior of AVs was modeled employing the Adaptive Cruise Control (ACC) car-following model, recently provided by PTV Group and embedded in VISSIM to better replicate AV behavior. The model includes eighteen adjustable behavioral parameters, among which *Min gap time* is provided to replicate the ACC controller in AVs. Other parameters, related to acceleration/deceleration limits or speed adaptation, were kept at their default values, as they primarily reflect general vehicle performance rather than driver-specific headway behavior. Therefore, only the minimum gap time was adjusted to align with the study's objectives on drivers' headway preferences. For brevity, further details about the model and the default values of other parameters are provided in [34].

To estimate the number of simulation runs, a power analysis was carried out in G*Power 3.1 [35]. To detect an effect size (f = 0.40) for both main and interaction effects at a significance level of $\alpha = 0.10$ and statistical power of $1 - \beta = 0.90$, at least 6 simulation runs were necessary. An $\alpha = 0.10$ was selected to balance Type I and Type II error risks in simulation-based traffic experiments, where variability between runs is low, and the main objective is to maintain sufficient sensitivity to detect meaningful effects. Therefore, the output of six simulation runs for each experimental scenario using different seed numbers was analyzed.

## 4. STATISTICAL ANALYSIS

The Analysis of Variance (ANOVA) was employed to test the effects of the independent variables including ACC Mode (Dynamic ACC *vs.* Fixed ACC) and AV MPR (0%, 25%, 50%, 75%, and 100%) on the dependent variables of average travel time (seconds), average speed (km/h), both measured between DPA1 and DP2 (Fig. **1**), and flow rate, defined as the total number of vehicles arriving at DP2 (Fig. **1**) during the simulation period. The normality assumption of the model residuals as a prerequisite for ANOVA [36] was evaluated using the commonly used graphical method of Q-Q plot. The Q-Q plots revealed that the residuals did not completely satisfy the normality assumption. To address this, several transformation approaches, including square root [37], Box-Cox [38], and logarithmic transformations, were applied. When these adjustments were insufficient to achieve normality, the Aligned Rank Transform (ART) ANOVA was employed, which allows testing both main and interaction effects of the independent variables on the dependent measures [39].

Moreover, the partial eta square ($\eta_p^2$) effect size was estimated for the main and interaction effects of the independent variables. The $\eta_p^2$ was interpreted based on the conventional thresholds, where an $\eta_p^2$ value between 0.01 and 0.06 is considered as a small effect, values from

0.06 up to 0.14 indicate a medium effect, and values greater than 0.14 represent a large effect size [40].

Post hoc comparisons using the estimated marginal means were performed, with the Tukey method [41] to adjust the significance level of $p$-values due to multiple comparisons and to control for Type I error. In addition, the Rank-biserial correlation ($r$) effect size was measured to reflect the degree of difference between the two pairs of comparisons based on ranks' scores [42]. It varies between -1 and 1 based on the differences between the pairs' ranks. Absolute $r$ values of 0.1 to 0.3 are associated with a small effect size, values from 0.3 to 0.5 represent a medium effect size, and values greater than 0.5 are interpreted as a large effect size. This method enabled pairwise comparisons while controlling for Type I error, ensuring that the observed differences could be interpreted reliably.

All statistical analyses were performed utilizing R (4.5.0) statistical software [43] with a significance level of $\alpha = 0.05$. The R packages of "ARTool" [39] and "emmeans" [44] were used for the analysis purposes.

## 5. RESULTS AND DISCUSSION

### 5.1. Effects of AVs on Average Travel Time

A two-way ART-ANOVA was performed following the failure of the residuals' normality assumption to statistically test the effects of independent variables on travel time as the dependent variable. As presented in Table **4**, the main effect of MPR on travel time was significant with a very large effect size [$F(4, 50) = 150.860$, $p < 0.001$, $\eta_p^2 = 0.920$]. Similarly, the main effect of ACC Mode had a significant main effect on travel time with a very large effect size [$F(1, 50) = 153.420$, $p < 0.001$, $\eta_p^2 = 0.750$], and its interaction with MPR also significantly affected travel time with a very large effect size [$F(4, 50) = 129.390$, $p < 0.001$, $\eta_p^2 = 0.910$].

As presented in Table **5**, a post hoc comparison using estimated marginal means from the ART-ANOVA for the main effect of MPR on travel time was performed. The results showed that travel time was significantly different between AV MPRs of 0% and 25% (mean difference = -12.000, $t$ = -5.607, $p$ < 0.001, $r$ = 0.850), between 0% and 50% (mean difference = -24.000, $t$ = -11.213, $p$ < 0.001, $r$ = 0.850), between 0% and 75% (mean difference = -44.667, $t$ = -20.869, $p$ < 0.001, $r$ = 0.850), and between 0% and 100% (mean difference = -39.333, $t$ = -18.377, $p$ < 0.001, $r$ = 0.850) all with very large effect sizes.

With respect to the main effect of ACC Mode, the results indicated that a significant difference between the Dynamic ACC and Fixed ACC modes existed with a medium to large effect size (mean difference = 30.000, $t$ = -12.386, $p$ < 0.001, $r$ = 0.344). In addition, the results of post hoc analyses for the interaction effect of ACC Mode and MPR, provided in Table **6**, indicated that at an AV MPR of 25%, travel time was different between the Dynamic and Fixed ACC modes with a medium to large effect size (mean difference = 6.000, $t$ = 3.517.823, $p$ < 0.050, $r$ = 0.432). Likewise, the differences in travel time between the Dynamic ACC and Fixed ACC groups were significant with very large effect sizes at AV MPRs of 50% (mean difference = 18.000, $t$ = 10.550, $p$ < 0.001, $r$ = 0.832), 75% (mean difference = 16.333, $t$ = 9.573, $p$ < 0.001, $r$ = 0.832), and 100% (mean difference = 19.667, $t$ = 11.527, $p$ < 0.001, $r$ = 0.832).

With the Dynamic ACC mode, the results showed that travel time was significantly different between AV MPRs of 0% and 25% (mean difference = -15.000, $t$ = -8.791, $p$ < 0.001, $r$ = 0.832), between 0% and 50% (mean difference = -39.000, $t$ = -22.858, $p$ < 0.001, $r$ = 0.832), between 0% and 75% (mean difference = -48.500, $t$ = -28.426, $p$ < 0.001, $r$ = 0.832), and between 0% and 100% (mean difference = -47.500, $t$ = -27.840, $p$ < 0.001, $r$ = 0.832) all with very large effect sizes. Similarly, under the Fixed ACC scenario, the differences in travel among AV MPRs of 0% and 25% (mean difference = -9.000, $t$ = -5.275, $p$ < 0.001, $r$ = 0.820), between 0% and 50% (mean difference = -21.000, $t$ = -12.308, $p$ < 0.001, $r$ = 0.832), between 0% and 75% (mean difference = -32.167, $t$ = -18.853, $p$ < 0.001, $r$ = 0.832), and between 0% and 100% (mean difference = -27.833, $t$ = -16.313, $p$ < 0.001, $r$ = 0.832) were significant with very large effect sizes. Table **6** presents the comparisons for all pairs.

As shown in Fig. (**2**), travel time is expressed as the percentage change relative to the baseline scenario (MPR = 0%), allowing a clear comparison of the impact of increasing AV penetration on traffic performance. With the increase in MPRs of AVs, travel time increases with respect to the baseline scenario, irrespective of the ACC mode. This aligns with the findings of previous studies indicating that the introduction of low-level AVs may result in higher travel time [23, 25]. In addition, the results showed that the Dynamic ACC setting leads to significantly higher travel times as the MPR of AVs increases, particularly when AVs constitute the majority of traffic flow. At an AV MPR of 50%, travel time increases by about 30% compared to the baseline, escalating sharply to about 55% at the AV MPR of 75%, before stabilizing at 100%. Although travel time also increases under the Fixed ACC scenario with increasing AV MPRs, the magnitude of change is much smaller, reaching a maximum of about 15% at an AV MPR of 75%. The difference between Dynamic and Fixed ACC grows with AV MPR, suggesting that dynamic headway adjustments increasingly disrupt the consistency of car-following behavior, leading to less harmonized traffic flow. These findings emphasize the importance of considering drivers' dynamic behavior in ACC modeling, as such adjustments can significantly worsen travel times, particularly under higher AV market penetration rates.

**Table 4. Results of ART-ANOVA for travel time.**

| Effect | df | df.res | F | *p*-value | $\eta_p^2$ |
|---|---|---|---|---|---|
| MPR | 4 | 50 | 150.860 | < 0.001 | 0.920 |
| ACC Mode | 1 | 50 | 153.420 | < 0.001 | 0.750 |
| ACC Mode: MPR | 4 | 50 | 129.390 | < 0.001 | 0.910 |

**Table 5. Tukey-adjusted pairwise MPR comparisons for travel time.**

| Contrast (MPR) | Mean. Diff | SE | *t* value | *p*-value | Effect Size (r) |
|---|---|---|---|---|---|
| 0%–25% | -12.000 | 2.140 | -5.607 | < 0.001 | 0.850 |
| 0%–50% | -24.000 | 2.140 | -11.213 | < 0.001 | 0.850 |
| 0%–75% | -44.667 | 2.140 | -20.869 | < 0.001 | 0.850 |
| 0%–100% | -39.333 | 2.140 | -18.377 | < 0.001 | 0.850 |
| 25%–50% | -12.000 | 2.140 | -5.607 | < 0.001 | 0.849 |
| 25%–75% | -32.667 | 2.140 | -15.262 | < 0.001 | 0.849 |
| 25%–100% | -27.333 | 2.140 | -12.770 | < 0.001 | 0.849 |
| 50%–75% | -20.667 | 2.140 | -9.656 | < 0.001 | 0.424 |
| 50%–100% | -15.333 | 2.140 | -7.164 | < 0.001 | 0.424 |
| 75%–100% | 5.333 | 2.140 | 2.492 | > 0.050 | 0.189 |

**Table 6. Pairwise comparisons for the interaction effect of ACC mode and MPR on travel time (tukey-adjusted).**

| Contrast (MPR in %) | Mean. Diff | SE | *t* value | *p*-value | Effect Size (r) |
|---|---|---|---|---|---|
| D-0% – D-25% | -15.000 | 1.706 | -8.791 | < 0.001 | 0.832 |
| D-0% – D-50% | -39.000 | 1.706 | -22.858 | < 0.001 | 0.832 |
| D-0% – D-75% | -48.500 | 1.706 | -28.426 | < 0.001 | 0.832 |
| D-0% – D-100% | -47.500 | 1.706 | -27.840 | < 0.001 | 0.832 |
| D-0% – F-0% | 0.000 | 1.706 | 0.000 | > 0.050 | 0.000 |
| D-25% – D-50% | -24.000 | 1.706 | -14.066 | < 0.001 | 0.832 |
| D-25% – D-75% | -33.500 | 1.706 | -19.634 | < 0.001 | 0.832 |
| D-25% – D-100% | -32.500 | 1.706 | -19.048 | < 0.001 | 0.832 |
| D-25% – F-25% | 6.000 | 1.706 | 3.517 | > 0.050 | 0.432 |
| D-50% – D-75% | -9.500 | 1.706 | -5.568 | > 0.050 | 0.832 |
| D-50% – D-100% | -8.500 | 1.706 | -4.982 | < 0.001 | 0.832 |
| D-50% – F-50% | 18.000 | 1.706 | 10.550 | < 0.001 | 0.832 |
| D-75% – D-100% | 1.000 | 1.706 | 0.586 | > 0.050 | 0.139 |
| D-75% – F-75% | 16.333 | 1.706 | 9.573 | < 0.001 | 0.832 |
| D-100% – F-100% | 19.667 | 1.706 | 11.527 | < 0.001 | 0.832 |
| F-0% – F-25% | -9.000 | 1.706 | -5.275 | < 0.001 | 0.820 |
| F-0% – F-50% | -21.000 | 1.706 | -12.308 | < 0.001 | 0.832 |
| F-0% – F-75% | -32.167 | 1.706 | -18.853 | < 0.001 | 0.832 |
| F-0% – F-100% | -27.833 | 1.706 | -16.313 | < 0.001 | 0.832 |
| F-25% – F-50% | -12.000 | 1.706 | -7.033 | < 0.001 | 0.832 |
| F-25% – F-75% | -23.167 | 1.706 | -13.578 | < 0.001 | 0.832 |
| F-25% – F-100% | -18.833 | 1.706 | -11.038 | < 0.001 | 0.832 |
| F-50% – F-75% | -11.167 | 1.706 | -6.545 | < 0.001 | 0.832 |
| F-50% – F-100% | -6.833 | 1.706 | -4.005 | < 0.010 | 0.832 |
| F-75% – F-100% | 4.333 | 1.706 | 2.540 | > 0.050 | 0.290 |

**Abbreviations:** D: Dynamic ACC; F: Fixed ACC.

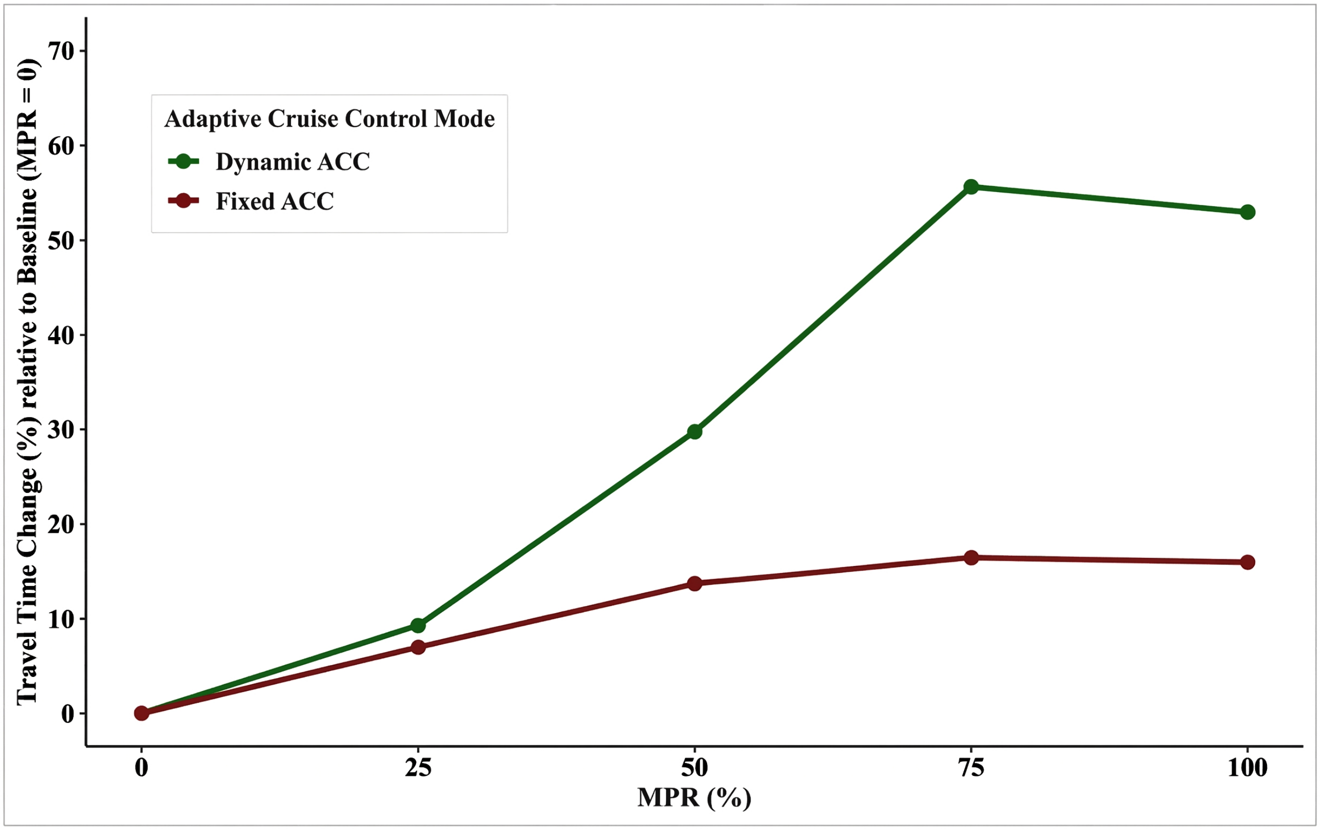


**Fig. (2).** Changes in travel time across varying AV MPRs by ACC mode.

### 5.2. Effects of AVs on Average Speed

As indicated in Table 7 the results of ART-ANOVA for speed as the dependent variable showed that a significant main effect of MPR was present with a very large effect size [$F(4, 50) = 273.200$, $p < 0.001$, $\eta_p^2 = 0.960$]. In addition, the main effect of ACC Mode on speed [$F(1, 50) = 155.240$, $p < 0.001$, $\eta_p^2 = 0.760$] and its interaction with MPR [$F(4, 50) = 222.660$, $p < 0.001$, $\eta_p^2 = 0.950$] were significant with very large effect sizes.

The results of post hoc analyses for the main effect of MPR showed that differences in speed between AV MPRs of 0% and 25% (mean difference = 12.000, $t = 7.417$, $p < 0.001$, $r = 0.780$), between 0% and 50% (mean difference = 36.417, $t = 22.508$, $p < 0.001$, $r = 0.850$), between 0% and 75% (mean difference = 47.583, $t = 29.410$, $p < 0.001$, $r = 0.850$), and between 0% and 100% (mean difference = 24.000, $t = 14.834$, $p < 0.001$, $r = 0.850$) were statistically significant with very large effect sizes. Table 8 shows the analyses results for all pairs.

The difference in speed between the Dynamic and Fixed ACC scenarios was also significant with a medium to large effect size (mean difference = -30.000, $t = -12.460$, $p < 0.001$, $r = 0.466$). Regarding the interaction effect of MPR and ACC Mode, the results indicated that at the AV MPR of 25%, the differences in speed between the Dynamic and Fixed ACC scenarios were significant with a very large effect size (mean difference = -18.000, $t = -8.356$, $p < 0.001$, $r = 0.832$). Similarly, a significant difference in speed between the Dynamic and Fixed ACC scenarios at AV MPRs of 50% (mean difference = -21.333, $t = -9.904$, $p < 0.001$, $r = 0.832$), 75% (mean difference = -19.333, $t = -8.975$, $p < 0.001$, $r = 0.832$), and 100% (mean difference = -22.667, $t = -10.523$, $p < 0.001$, $r = 0.832$) was present with very large effect sizes.

**Table 7. Results of ART-ANOVA for speed.**

| Effect | df | df.res | F | *p*-value | $\eta_p^2$ |
|---|---|---|---|---|---|
| MPR | 4 | 50 | 273.200 | < 0.001 | 0.960 |
| ACC Mode | 1 | 50 | 155.240 | < 0.001 | 0.760 |
| ACC Mode: MPR | 4 | 50 | 222.660 | < 0.001 | 0.950 |

**Table 8. Tukey-adjusted pairwise MPR comparisons for speed.**

| Contrast (MPR) | Mean. Diff | SE | *t* value | *p*-value | Effect Size (r) |
|---|---|---|---|---|---|
| 0%–25% | 12.000 | 1.618 | 7.417 | < 0.001 | 0.780 |
| 0%–50% | 36.417 | 1.618 | 22.508 | < 0.001 | 0.850 |
| 0%–75% | 47.583 | 1.618 | 29.410 | < 0.001 | 0.850 |
| 0%–100% | 24.000 | 1.618 | 14.834 | < 0.001 | 0.850 |
| 25%–50% | 24.417 | 1.618 | 15.091 | < 0.001 | 0.601 |
| 25%–75% | 35.583 | 1.618 | 21.993 | < 0.001 | 0.731 |
| 25%–100% | 12.000 | 1.618 | 7.417 | < 0.001 | 0.365 |
| 50%–75% | 11.167 | 1.618 | 6.902 | < 0.001 | 0.412 |
| 50%–100% | -12.417 | 1.618 | -7.674 | < 0.001 | 0.424 |
| 75%–100% | -23.583 | 1.618 | -14.576 | > 0.050 | 0.460 |

**Table 9. Pairwise comparisons for the interaction effect of ACC mode and MPR on speed (tukey-adjusted).**

| Contrast (MPR) | Mean. Diff | SE | *t* value | *p*-value | Effect Size (r) |
|---|---|---|---|---|---|
| D-0% – D-25% | 27.000 | 2.154 | 12.534 | < 0.001 | 0.832 |
| D-0% – D-50% | 45.000 | 2.154 | 20.891 | < 0.001 | 0.832 |
| D-0% – D-75% | 51.000 | 2.154 | 23.676 | < 0.001 | 0.832 |
| D-0% – D-100% | 37.667 | 2.154 | 17.486 | < 0.001 | 0.832 |
| D-0% – F-0% | 0.000 | 2.154 | 0.000 | > 0.050 | 0.000 |
| D-25% – D-50% | 18.000 | 2.154 | 8.356 | < 0.001 | 0.832 |
| D-25% – D-75% | 24.000 | 2.154 | 11.142 | < 0.001 | 0.832 |
| D-25% – D-100% | 10.667 | 2.154 | 4.952 | < 0.001 | 0.601 |
| D-25% – F-25% | -18.000 | 2.154 | -8.356 | < 0.001 | 0.832 |
| D-50% – D-75% | 6.000 | 2.154 | 2.785 | > 0.050 | 0.832 |
| D-50% – D-100% | -7.333 | 2.154 | -3.404 | < 0.050 | 0.832 |
| D-50% – F-50% | -21.333 | 2.154 | -9.904 | < 0.001 | 0.832 |
| D-75% – D-100% | -13.333 | 2.154 | -6.190 | < 0.001 | 0.832 |
| D-75% – F-75% | -19.333 | 2.154 | -8.975 | < 0.001 | 0.832 |
| D-100% – F-100% | -22.667 | 2.154 | -10.523 | < 0.001 | 0.832 |
| F-0% – F-25% | 9.000 | 2.154 | 4.178 | < 0.010 | 0.760 |
| F-0% – F-50% | 23.667 | 2.154 | 10.987 | < 0.001 | 0.832 |
| F-0% – F-75% | 31.667 | 2.154 | 14.701 | < 0.001 | 0.832 |
| F-0% – F-100% | 15.000 | 2.154 | 6.964 | < 0.001 | 0.832 |
| F-25% – F-50% | 14.667 | 2.154 | 6.809 | < 0.001 | 0.832 |
| F-25% – F-75% | 22.667 | 2.154 | 10.523 | < 0.001 | 0.832 |
| F-25% – F-100% | 6.000 | 2.154 | 2.785 | > 0.050 | 0.832 |
| F-50% – F-75% | 8.000 | 2.154 | 3.714 | < 0.050 | 0.786 |
| F-50% – F-100% | -8.667 | 2.154 | -4.023 | < 0.010 | 0.832 |
| F-75% – F-100% | -16.667 | 2.154 | -7.737 | < 0.001 | 0.832 |

**Note:** D: Dynamic ACC; F: Fixed ACC.

Under the Dynamic ACC scenario, the differences in speed between AV MPRs of 0% and 25% (mean difference = 27.000, $t$ = 12.534, $p$ < 0.001, $r$ = 0.832), between 0% and 50% (mean difference = 45.000, $t$ = 20.891, $p$ < 0.001, $r$ = 0.832), between 0% and 75% (mean difference = 51.000, $t$ = 23.676, $p$ < 0.001, $r$ = 0.832), and between 0% and 100% (mean difference = 37.667, $t$ = 17.486, $p$ < 0.001, $r$ = 0.832) were significant with very large effect sizes. Similarly, in the Fixed ACC scenario, the results showed that speed was significantly different between AV MPR of 0% and 25% with a large effect size (mean difference = 9.000, $t$ = 4.178, $p$ < 0.001, $r$ = 0.760). Likewise, the differences in speed between AV MPRs of 0% and 50% (mean difference = 23.667, $t$ = 10.987, $p$ < 0.001, $r$ = 0.832), between 0% and 75% (mean difference = 31.667, $t$ = 14.701, $p$ < 0.001, $r$ = 0.832), and between 0% and 100% (mean difference = 15.000, $t$ = 6.964, $p$ < 0.001, $r$ = 0.832) were statistically significant with very large effect sizes. The results for all pairs are presented in Table **9**.

Figure **3** shows the impact of AV MPR on average speed under two ACC modes, highlighting the comparative trends between Dynamic ACC and Fixed ACC. As the AV MPR increases, speed consistently decreases relative to the baseline scenario (0% AVs), demonstrating that the effect of AVs on speed is dependent on both MPR and ACC mode. While Lu *et al.* [23] found that AVs improve speed, the results suggest that the introduction of AVs can lead to a reduction in speed. The apparent contradiction likely arises from differences in assumptions about AV driving styles and the choice of ACC mode. The findings of the present study may be more relevant, as in low-level AVs, the driving style is determined entirely by the human user. Assigning a range of driving styles based on drivers' observed behavior and their preferences in changing the ACC settings, therefore, reflects reality more closely. In the Dynamic ACC scenario, speed decreases almost linearly with increasing AV MPR, reaching a maximum reduction of approximately 30% at 75% MPR, before slightly stabilizing at 100% MPR. In contrast, the Fixed ACC scenario exhibits a more moderate decrease, with a maximum speed reduction of about 10% at 75% MPR. The larger reduction in speed under Dynamic ACC reflects the responsiveness of human drivers in adjusting headway settings, which can lead to more cautious driving as AV presence increases.

These results show that Dynamic ACC leads to more pronounced speed reductions than Fixed ACC across all MPR levels, highlighting how the flexibility of human-driven ACC adjustments magnifies the effect of AVs on speed. The patterns also parallel those observed for travel time, though the magnitude of speed reduction is slightly smaller.

### 5.3. Effects of AVs on Flow Rate

The results of ART-ANOVA for the dependent variable of Flow Rate, presented in Table 10, indicated that the main effect of MPR on flow rate was significant with a very large effect size [$F(4, 50) = 77.070$, $p < 0.001$, $\eta_p^2 = 0.860$]. Similarly, the main effect of ACC Mode on flow rate [$F(1, 50) = 134.976$, $p < 0.001$, $\eta_p^2 = 0.730$] as well as the interaction effect of ACC Mode and MPR on flow rate [$F(4, 50) = 28.675$, $p < 0.001$, $\eta_p^2 = 0.700$] were found to be significant with very large effect size.

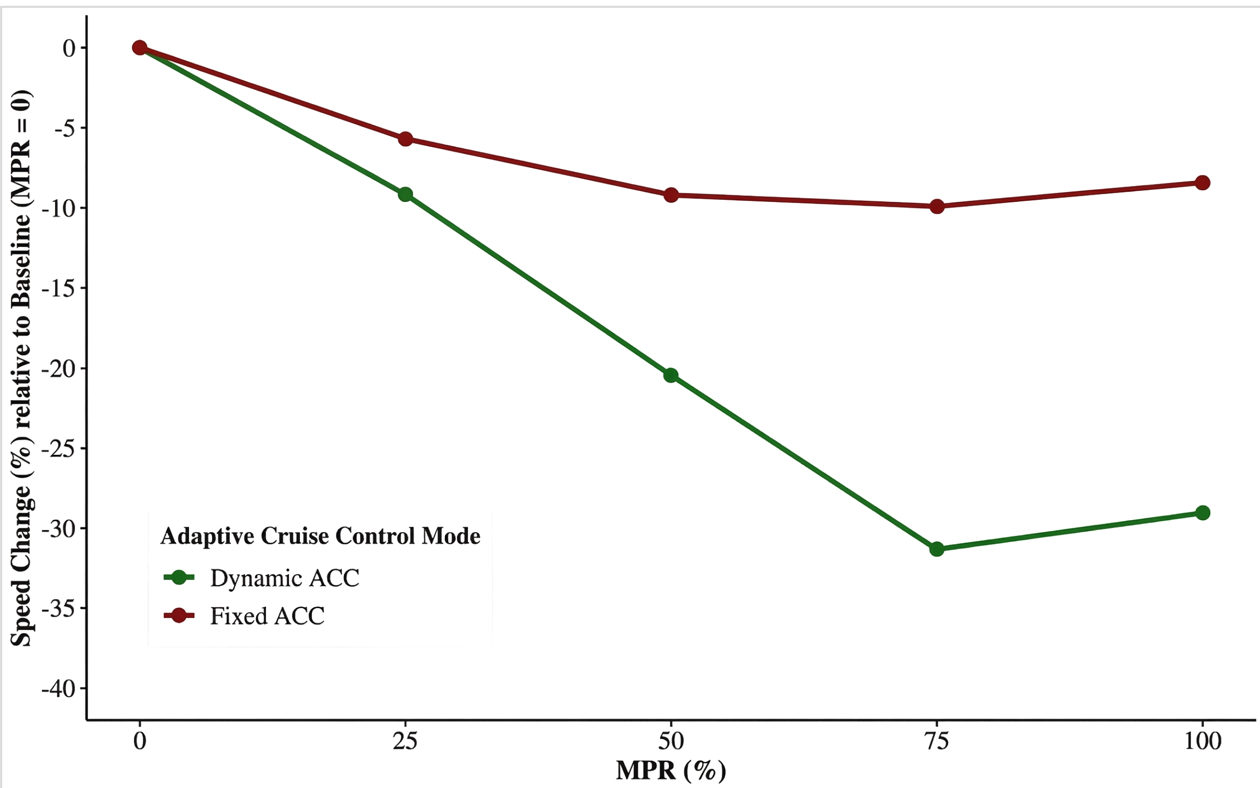


**Fig. (3).** Changes in speed across varying AV MPRs by ACC mode.

**Table 10. Results of ART-ANOVA for flow rate.**

| Effect | df | df.res | F | *p*-value | $\eta_p^2$ |
|---|---|---|---|---|---|
| MPR | 4 | 50 | 77.070 | < 0.001 | 0.860 |
| ACC Mode | 1 | 50 | 134.976 | < 0.001 | 0.730 |
| ACC Mode: MPR | 4 | 50 | 28.675 | < 0.001 | 0.700 |

Pairwise comparisons for the main effect of MPR showed that the difference in flow rate between AV MPRs of 0% and 25% was nonsignificant (mean difference = 5.667, $t$ = 1.959, $p$ > 0.050, $r$ = 0.330). However, the difference in flow rate between AV MPRs of 0% and 50% was significant with a large effect size (mean difference = 16.333, $t$ = 5.647, $p$ < 0.001, $r$ = 0.567). Similarly, significant differences in flow rate existed between AV MPRs of 0% and 75% (mean difference = 31.333, $t$ = 10.833, $p$ < 0.001, $r$ = 0.850) and between 0% and 100% (mean difference = 43.332, $t$ = 14.982, $p$ < 0.001, $r$ = 0.850) with very large effect sizes. Table **11** shows the results of post hoc analysis for the main effect of MPR on flow rate.

With respect to the effect of ACC Mode on flow rate, the results showed that flow rate was significantly different between the Dynamic and Fixed ACC modes with a small effect size (mean difference = -29.533, $t$ = -11.618, $p$ < 0.001, $r$ = 0.160). However, the pairwise comparisons for the interaction effect of ACC Mode and MPR on flow rate showed that no differences exist between the Dynamic and Fixed ACC settings at AV MPRs of 25% (mean difference = -1.667, $t$ = -0.427, $p$ > 0.050, $r$ = 0.139), 50% (mean difference = -8.333, $t$ = -1.675, $p$ > 0.050, $r$ = 0.220), 75% (mean difference = -6.000, $t$ = -1.539, $p$ > 0.050, $r$ = 0.168), and 100% (mean difference = -6.000, $t$ = -1.539, $p$ > 0.050, $r$ = 0.168).

Regarding the Dynamic ACC mode, the difference in flow rate between AV MPRs of 0% and 25% was nonsignificant (mean difference = 6.667, $t$ = 1.710, $p$ > 0.050, $r$ = 0.324), while the differences in flow rate between AV MPRs of 0% and 50% (mean difference = 20.333, $t$ = 5.214, $p$ < 0.001, $r$ = 0.834), between 0% and 75% (mean difference = 33.333, $t$ = 8.548, $p$ < 0.001, $r$ = 0.832), and between 0% and 100% (mean difference = 45.333, $t$ = 11.625, $p$ < 0.001, $r$ = 0.834) were significant with very large effect sizes. Under the Fixed ACC scenario, the differences in flow rate between AV MPRs of 0% and 25% (mean difference = 5.000, $t$ = 1.282, $p$ > 0.050, $r$ = 0.324) as well as between 0% and 50% (mean difference = 6.000, $t$ = 1.539, $p$ > 0.050, $r$ = 0.277) were not statistically significant. However, flow rate was statistically different between AV MPRs of 0% and 75% (mean difference = 27.333, $t$ = 7.009, $p$ < 0.001, $r$ = 0.832) and between 0% and 100% (mean difference = 39.333, $t$ = 10.086, $p$ < 0.001, $r$ = 0.832) with very large effect sizes. Table **12** presents the results of post hoc analyses for all pairs of interaction effects of CC Mode and MPR on flow rate.

**Table 11. Tukey-adjusted pairwise MPR comparisons for flow rate.**

| Contrast (MPR) | Mean. Diff | SE | *t*-value | *p*-value | Effect Size (r) |
|---|---|---|---|---|---|
| 0%–25% | 5.667 | 2.892 | 1.959 | > 0.050 | 0.330 |
| 0%–50% | 16.333 | 2.892 | 5.647 | < 0.001 | 0.567 |
| 0%–75% | 31.333 | 2.892 | 10.833 | < 0.001 | 0.850 |
| 0%–100% | 43.333 | 2.892 | 14.982 | < 0.001 | 0.850 |
| 25%–50% | 10.667 | 2.892 | 3.688 | < 0.010 | 0.401 |
| 25%–75% | 25.667 | 2.892 | 8.874 | < 0.001 | 0.849 |
| 25%–100% | 37.667 | 2.892 | 13.023 | < 0.001 | 0.849 |
| 50%–75% | 15.000 | 2.892 | 5.186 | < 0.001 | 0.849 |
| 50%–100% | 27.000 | 2.892 | 9.335 | < 0.001 | 0.849 |
| 75%–100% | 12.000 | 2.892 | 4.149 | < 0.001 | 0.849 |

**Table 12. Pairwise comparisons for the interaction effect of cruise control mode and MPR on flow rate (tukey-adjusted).**

| Contrast (MPR in %) | Mean. Diff | SE | *t* value | *p*-value | Effect Size (r) |
|---|---|---|---|---|---|
| D-0% – D-25% | 6.667 | 3.900 | 1.710 | > 0.050 | 0.324 |
| D-0% – D-50% | 20.333 | 3.900 | 5.214 | < 0.001 | 0.834 |
| D-0% – D-75% | 33.333 | 3.900 | 8.548 | < 0.001 | 0.832 |
| D-0% – D-100% | 45.333 | 3.900 | 11.625 | < 0.001 | 0.834 |
| D-0% – F-0% | 0.000 | 3.900 | 0.000 | > 0.050 | 0.000 |
| D-25% – D-50% | 13.667 | 3.900 | 3.505 | < 0.050 | 0.741 |
| D-25% – D-75% | 26.667 | 3.900 | 6.838 | < 0.001 | 0.832 |
| D-25% – D-100% | 38.667 | 3.900 | 9.915 | < 0.001 | 0.834 |
| D-25% – F-25% | -1.667 | 3.900 | -0.427 | > 0.050 | 0.139 |
| D-50% – D-75% | 13.000 | 3.900 | 3.334 | < 0.050 | 0.834 |
| D-50% – D-100% | 25.000 | 3.900 | 6.411 | < 0.001 | 0.835 |
| D-50% – F-50% | -8.333 | 3.900 | -1.675 | > 0.050 | 0.220 |
| D-75% – D-100% | 12.000 | 3.900 | 2.077 | > 0.050 | 0.834 |

*(Table 12) contd.....*

| Contrast (MPR in %) | Mean. Diff | SE | *t* value | *p*-value | Effect Size (r) |
|---|---|---|---|---|---|
| D-75% – F-75% | -6.000 | 3.900 | -1.539 | > 0.050 | 0.168 |
| D-100% – F-100% | -6.000 | 3.900 | -1.539 | > 0.050 | 0.168 |
| F-0% – F-25% | 5.000 | 3.900 | 1.282 | > 0.050 | 0.324 |
| F-0% – F-50% | 6.000 | 3.900 | 1.539 | > 0.050 | 0.277 |
| F-0% – F-75% | 27.333 | 3.900 | 7.009 | < 0.001 | 0.832 |
| F-0% – F-100% | 39.333 | 3.900 | 10.086 | < 0.001 | 0.832 |
| F-25% – F-50% | 1.000 | 3.900 | 0.256 | > 0.050 | 0.046 |
| F-25% – F-75% | 22.333 | 3.900 | 5.727 | < 0.001 | 0.834 |
| F-25% – F-100% | 34.333 | 3.900 | 8.804 | < 0.001 | 0.834 |
| F-50% – F-75% | 21.333 | 3.900 | 5.470 | < 0.001 | 0.832 |
| F-50% – F-100% | 33.333 | 3.900 | 8.548 | < 0.010 | 0.832 |
| F-75% – F-100% | 12.000 | 3.900 | 3.077 | > 0.050 | 0.670 |

**Abbreviations:** D: Dynamic ACC; F: Fixed ACC.

Figure **4** shows the impact of AV MPRs on flow rate, expressed as the percentage of changes relative to the baseline scenario (MPR = 0%). The trends in flow rates under the Dynamic and Fixed ACC scenarios. Regardless of cruise control settings, flow rates remain relatively stable with the introduction of AVs up to an AV MPR of 50%, indicating that low to moderate AV deployment does not substantially affect traffic flow. However, at higher AV MPRs, flow rates decrease almost linearly. In the Dynamic ACC scenario, the largest reduction occurs at 100% AV MPR, with flow rates decreasing by approximately 25% relative to the baseline. In the Fixed ACC scenario, the reduction is more moderate, demonstrating that the flexibility of human drivers in adjusting ACC settings (Dynamic ACC) amplifies the impact of AV penetration on flow rate. These results are consistent with Shang and Stern [24], who reported that commercially available AVs can negatively affect roadway capacity, with reductions of up to approximately 35%. In our study, increasing the MPR of AVs led to a decrease in flow rate. Although flow rate is not synonymous with capacity, the combination of reduced speeds and lower flow rates aligns with the capacity reduction observed by Shang and Stern [24].

Generally, Figure **4** shows that Dynamic ACC results in more pronounced reductions in flow rate across all AV MPR levels, while Fixed ACC shows a moderate decline.

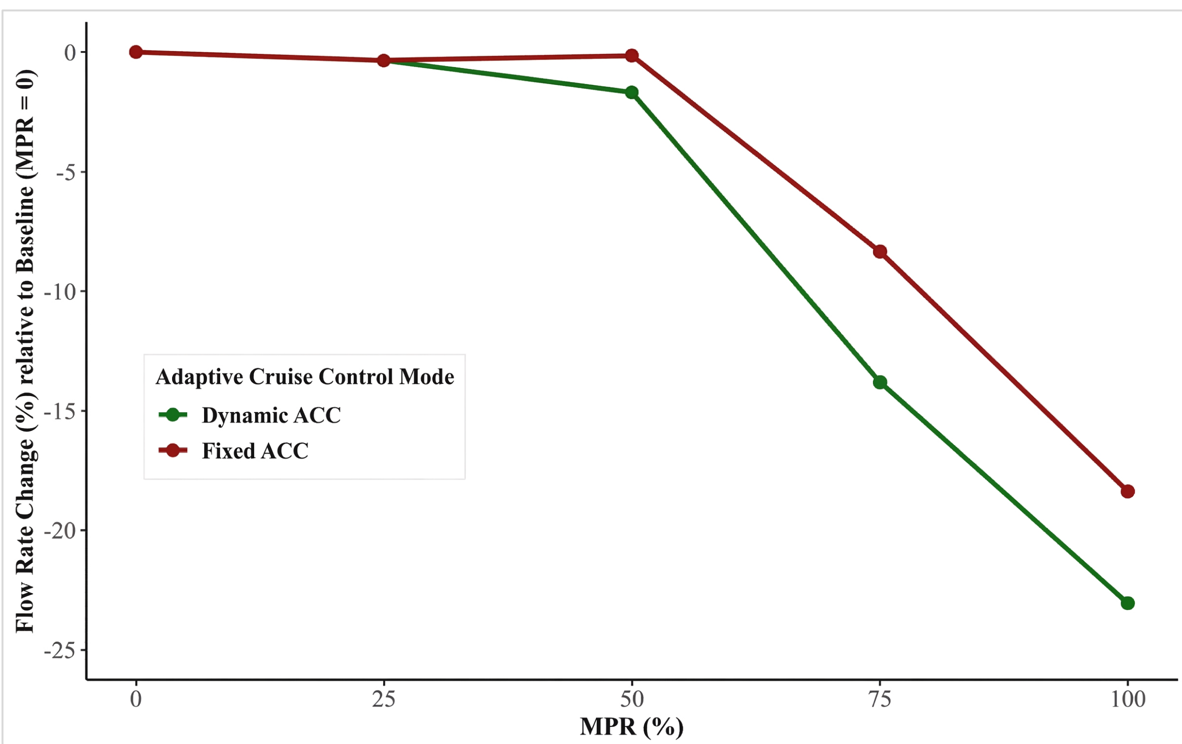


**Fig. (4).** Changes in flow rate across varying AV MPRs by ACC mode.

Overall, the results indicate that traffic performance declines under the Dynamic ACC scenario as the MPR of AVs increases. This effect is likely due to the variability in headway adjustments, which disrupts consistent car-following behavior and reduces traffic harmonization. Frequent changes in headway settings can create irregular gaps between vehicles, increase speed fluctuations, and amplify stop-and-go waves, ultimately leading to longer average travel times and reduced flow efficiency on highways.

## CONCLUSION

This study aimed to explore the effect of Level 2 AVs, which are equipped with the adaptive cruise control feature, across varying market penetration rates ranging from no AV (MPR = 0%) to full AV (MPR = 100%), on traffic efficiency under the Dynamic and Fixed ACC scenarios. Specifically, the study investigated how these two ACC settings influence average travel time, average speed, and flow rate at different AV MPRs. The results indicated the following:

- The increase in MPR of Level 2 AVs resulted in higher average travel time, reduced average speed, and decreased flow rate, rejecting $H_1$, $H_2$, and $H_3$, respectively.
- Average travel time was significantly higher in the Dynamic ACC scenario compared to the Fixed ACC scenario at AV MPRs of 50%, 75%, and 100%, with very large effect sizes, hence partially supporting $H_4$, since the difference in average travel time under the Dynamic and Fixed ACC scenarios remained the same at an AV MPR of 25%.
- Average speed with the Dynamic ACC setting was significantly smaller compared to the Fixed ACC mode at AV MPRs of 25%, 50%, 75%, and 100%, therefore confirming $H_5$.
- Flow rate remained unchanged across the Dynamic and Fixed ACC scenarios at all AV MPRs, leading to the rejection of $H_6$.

Overall, the results indicate that the introduction of low-level AVs negatively impacts traffic efficiency by increasing travel time and reducing speed and flow rates. Dynamically changing the headway settings in Level 2 AVs during driving disrupts the steadiness of car-following, further reducing speed and increasing travel time. Beyond the ACC settings, the study showed that when AVs follow a range of driving styles, similar to what is observed among ACC users, traffic efficiency metrics can decline. This could explain why earlier studies reported improvements in traffic efficiency metrics since they usually considered only a single, uniform AV driving style rather than a realistic mixture.

In future work, these findings could be extended by considering infrastructure and surface-related factors that may interact with AV behavior. Praticò *et al.* [45] demonstrated that road friction decay requires dynamic adjustments to speed limits, and that under certain conditions, AVs may be forced to operate at lower speeds than human-driven vehicles to preserve safety margins. While our study shows that increasing AV MPR can reduce speed and flow rate, particularly under Dynamic ACC settings, a logical next step is to examine how such speed reductions might be amplified or mitigated under varying pavement friction, weather conditions, and geometric design parameters.

This study explored how ACC users could adapt their headway settings dynamically in hypothetical scenarios. Nonetheless, further research is required to confirm how drivers actually modify their headway preferences under varying traffic and environmental conditions.

## AUTHORS' CONTRIBUTIONS

The authors confirm their contributions to the paper as follows: M.G.: Conceptualization was performed; M.S. and R.C.: Analysis and interpretation of the results were carried out; R.R.: Validation was conducted; G.G.: Draft manuscript was prepared. All authors reviewed the results and approved the final version of the manuscript.

## LIST OF ABBREVIATIONS

| | | |
|---|---|---|
| AV | = | Automated Vehicles |
| ACC | = | Adaptive Cruise Control |
| CACC | = | Cooperative Adaptive Cruise Control |
| MPR | = | Market Penetration Rate |
| ANOVA | = | Analysis of Variance |
| HDVs | = | Human-Driven Vehicles |
| SAE | = | Society of Automotive Engineers |

## CONSENT FOR PUBLICATION

Not applicable.

## AVAILABILITY OF DATA AND MATERIALS

The data and supportive information are available within the article.

## FUNDING

This study was supported by the University of Padua (project "HuMap" – ROSS_BIRD2222_01, granted to RR, and project CECC_BIRD23_02, granted to RC). The study was carried out within the scope of the project "Smart Engineering Infrastructures (SEI ICEA)," for which the Department of Civil, Environmental, and Architectural Engineering of the University of Padua has been recognized as "University Department of Excellence" by the Ministry of University and Research, Italy.

## CONFLICT OF INTEREST

Drs. Riccardo Ceccato and Massimiliano Gastaldi, are the Editorial Board Members of The Open Transportation Journal.

## ACKNOWLEDGEMENTS

Declared none.

## REFERENCES


[1] S. Becker, S. Brandenburg, and M. Thüring, "Driver-initiated take-overs during critical evasion maneuvers in automated driving", *Accid. Anal. Prev.,* vol. 194, p. 107362, 2024. [http://dx.doi.org/10.1016/j.aap.2023.107362] [PMID: 37931430]

[2] C. Wang, F. Guo, S. Zhao, Z. Zhu, and Y. Zhang, "Safety assessment for autonomous vehicles: A reference driver model for highway merging scenarios", *Accid. Anal. Prev.,* vol. 206, p. 107710, 2024. [http://dx.doi.org/10.1016/j.aap.2024.107710] [PMID: 39018627]

[3] L. Luo, Y. Liu, Y. Feng, H.X. Liu, and Y.E. Ge, "Stabilizing traffic flow by autonomous vehicles: Stability analysis and implementation considerations", *Transp. Res., Part C Emerg. Technol.,* vol. 158, p. 104449, 2024. [http://dx.doi.org/10.1016/j.trc.2023.104449]

[4] J. Singh, A. Sharma, A. Sharma, and S. Kaur, "Autonomous driving and ADAS embedded with AI: Comparing the AI norms", *2024 International Conference on Intelligent Systems for Cybersecurity (ISCS)* Gurugram, India, 04 May 2024, pp. 1–6. [http://dx.doi.org/10.1109/ISCS61804.2024.10581391]

[5] M. Saljoqi, R. Ceccato, F. Orsini, R. Rossi, and M. Gastaldi, "Emerging behavioral adaptation of human-driven vehicles in interactions with automated vehicles: Insights from a microsimulation study", *Future Transportation,* vol. 5, no. 3, p. 124, 2025. [http://dx.doi.org/10.3390/futuretransp5030124]

[6] S.A. Bagloee, M. Tavana, M. Asadi, and T. Oliver, "Autonomous vehicles: Challenges, opportunities, and future implications for transportation policies", *Journal of Modern Transportation,* vol. 24, no. 4, pp. 284-303, 2016. [http://dx.doi.org/10.1007/s40534-016-0117-3]

[7] D.J. Fagnant, and K. Kockelman, "Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations", *Transp. Res. Part A Policy Pract.,* vol. 77, pp. 167-181, 2015. [http://dx.doi.org/10.1016/j.tra.2015.04.003]

[8] N. Raju, W. Schakel, N. Reddy, Y. Dong, and H. Farah, "Car-Following properties of a commercial adaptive cruise control system: A pilot field test", *Transp. Res. Rec.,* vol. 2676, no. 7, pp. 128-143, 2022. [http://dx.doi.org/10.1177/03611981221077085]

[9] M. Natarajan, K. Akash, and T. Misu, "Toward adaptive driving styles for automated driving with users' trust and preferences", *2022 17th ACM/IEEE International Conference on Human-Robot Interaction (HRI)* Sapporo, Japan, 10 March 2022, pp. 940–944. [http://dx.doi.org/10.1109/HRI53351.2022.9889313]

[10] Z. Ma, and Y. Zhang, "Drivers trust, acceptance, and takeover behaviors in fully automated vehicles: Effects of automated driving styles and driver's driving styles", *Accid. Anal. Prev.,* vol. 159, p. 106238, 2021. [http://dx.doi.org/10.1016/j.aap.2021.106238] [PMID: 34182321]

[11] M. Saljoqi, F. Orsini, R. Rossi, and M. Gastaldi, "From manual to automated driving: Understanding the shift in driver headway preferences", *Transp. Res. Procedia,* vol. 86, pp. 676-683, 2025. [http://dx.doi.org/10.1016/j.trpro.2025.04.084]

[12] L. Vasile, B. Seitz, V. Staab, M. Liebherr, C. Däsch, and D. Schramm, "Influences of personal driving styles and experienced system characteristics on driving style preferences in automated driving", *Appl. Sci.,* vol. 13, no. 15, p. 8855, 2023. [http://dx.doi.org/10.3390/app13158855]

[13] E. Aria, J. Olstam, and C. Schwietering, "Investigation of automated vehicle effects on driver's behavior and traffic performance", *Transp. Res. Procedia,* vol. 15, pp. 761-770, 2016. [http://dx.doi.org/10.1016/j.trpro.2016.06.063]

[14] E. Szimba, and M. Hartmann, "Assessing travel time savings and user benefits of automated driving – A case study for a commuting relation", *Transp. Policy,* vol. 98, pp. 229-237, 2020. [http://dx.doi.org/10.1016/j.tranpol.2020.03.007]

[15] M.H. Rahman, M. Abdel-Aty, and Y. Wu, "A multi-vehicle communication system to assess the safety and mobility of connected and automated vehicles", *Transp. Res., Part C Emerg. Technol.,* vol. 124, p. 102887, 2021. [http://dx.doi.org/10.1016/j.trc.2020.102887]

[16] A. Spiliopoulou, D. Manolis, F. Vandorou, and M. Papageorgiou, "Adaptive cruise control operation for improved motorway traffic flow", *Transp. Res. Rec.,* vol. 2672, no. 22, pp. 24-35, 2018. [http://dx.doi.org/10.1177/0361198118796020]

[17] A. Rezaei, and B. Caulfield, "Simulating a transition to autonomous mobility", *Simul. Model. Pract. Theory,* vol. 106, p. 102175, 2021. [http://dx.doi.org/10.1016/j.simpat.2020.102175]

[18] J.E. Park, W. Byun, Y. Kim, H. Ahn, and D.K. Shin, "The impact of automated vehicles on traffic flow and road capacity on urban road networks", *J. Adv. Transp.,* vol. 2021, no. 1, pp. 1-10, 2021. [http://dx.doi.org/10.1155/2021/8404951]

[19] Y. Li, S. Zhang, Y. Pan, B. Zhou, and Y. Peng, "Exploring the stability and capacity characteristics of mixed traffic flow with autonomous and human-driven vehicles considering aggressive driving", *J. Adv. Transp.,* vol. 2023, pp. 1-21, 2023. [http://dx.doi.org/10.1155/2023/2578690]

[20] A.D. Beza, M.M. Zefreh, A. Torok, and A.A. Mekonnen, "How PTV vissim has been calibrated for the simulation of automated vehicles in literature?", *Adv. Civ. Eng.,* vol. 2022, no. 1, p. 2548175, 2022. [http://dx.doi.org/10.1155/2022/2548175]

[21] M.M. Minderhoud, and P.H.L. Bovy, "Impact of intelligent cruise control on motorway capacity", *Transp. Res. Rec.,* vol. 1679, no. 1, pp. 1-9, 1999. [http://dx.doi.org/10.3141/1679-01]

[22] N.K. Sekar, V. Malaghan, and D.S. Pawar, "Micro-simulation insights into the safety and operational benefits of autonomous vehicles", *J. Intell. Connect. Veh.,* vol. 6, no. 4, pp. 202-210, 2023. [http://dx.doi.org/10.26599/JICV.2023.9210007]

[23] Q.L. Lu, M. Qurashi, D. Varesanovic, J. Sodnik, and C. Antoniou, "Exploring the influence of automated driving styles on network efficiency", *Transp. Res. Procedia,* vol. 52, pp. 380-387, 2021. [http://dx.doi.org/10.1016/j.trpro.2021.01.094]

[24] M. Shang, and R.E. Stern, "Impacts of commercially available adaptive cruise control vehicles on highway stability and throughput", *Transp. Res., Part C Emerg. Technol.,* vol. 122, no. 102897, p. 102897, 2021. [http://dx.doi.org/10.1016/j.trc.2020.102897]

[25] M. Saljoqi, R. Ceccato, G. Gecchele, R. Rossi, and M. Gastaldi, "Network-level analysis of the effects of drivers' preferences toward driving behavior of Automated Vehicles: A microsimulation study on a highway segment", *Transp. Res. Procedia,* vol. 90, pp. 336-343, 2025. [http://dx.doi.org/10.1016/j.trpro.2025.06.135]

[26] K. Mattas, M. Makridis, P. Hallac, M.A. Raposo, C. Thiel, T. Toledo, and B. Ciuffo, "Simulating deployment of connectivity and automation on the Antwerp ring road", *IET Intell. Transp. Syst.,* vol. 12, no. 9, pp. 1036-1044, 2018. [http://dx.doi.org/10.1049/iet-its.2018.5287]

[27] Y. Lei, K. Liu, Y. Fu, X. Li, Z. Liu, and S. Sun, "Research on driving style recognition method based on driver's dynamic demand", *Adv. Mech. Eng.,* vol. 8, no. 9, p. 1687814016670577, 2016. [http://dx.doi.org/10.1177/1687814016670577]

[28] L. Ma, S. Qu, L. Song, J. Zhang, and J. Ren, "Human-like car-following modeling based on online driving style recognition", *Electronic Research Archive,* vol. 31, no. 6, pp. 3264-3290, 2023. [http://dx.doi.org/10.3934/era.2023165]

[29] F. Yan, M. Liu, C. Ding, Y. Wang, and L. Yan, "Driving style recognition based on electroencephalography data from a simulated driving experiment", *Front. Psychol.,* vol. 10, p. 1254, 2019. [http://dx.doi.org/10.3389/fpsyg.2019.01254] [PMID: 31191419]

[30] M. Pereira, M. Beggiato, and T. Petzoldt, "Use of adaptive cruise control functions on motorways and urban roads: Changes over time in an on-road study", *Appl. Ergon.,* vol. 50, pp. 105-112,

2015. [http://dx.doi.org/10.1016/j.apergo.2015.03.002] [PMID: 25959324]

[31] J.F. Hair, W.C. Black, B.J. Babin, and R.E. Anderson, *Multivariate data analysis.,* 8th ed Cengage: Andover, Hampshire, 2019.

[32] F.G. Praticò, R. Vaiana, and V. Gallelli, "Transport and traffic management by micro simulation models: Operational use and performance of roundabouts", *Urban Transp.,* vol. XVIII, pp. 383-394, 2012. [http://dx.doi.org/10.2495/UT120331]

[33] K. Aghabayk, M. Sarvi, W. Young, and L. Kautzsch, "A novel methodology for evolutionary calibration of VISSIM by multi-threading", *Australasian Transport Research Forum 2013 Proceedings* Brisbane, Australia, 2013, 2–4 October.

[34] "Multimodal traffic simulation software", Available from:https://www.ptvgroup.com/en/products/ptv-vissim

[35] F. Faul, E. Erdfelder, A. Buchner, and A.G. Lang, "Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses", *Behav. Res. Methods,* vol. 41, no. 4, pp. 1149-1160, 2009. [http://dx.doi.org/10.3758/BRM.41.4.1149] [PMID: 19897823]

[36] D.C. Montgomery, *Design and Analysis of Experiments.,* 9th ed John Wiley & Sons, Inc.: Hoboken, NJ, 2017.

[37] M.S. Bartlett, "The square root transformation in analysis of variance", *J. R. Stat. Soc. Series B Stat. Methodol.,* vol. 3, no. 1, pp. 68-78, 1936. [http://dx.doi.org/10.2307/2983678]

[38] G.E.P. Box, and D.R. Cox, "An Analysis of Transformations", *J. R. Stat. Soc. Series B Stat. Methodol.,* vol. 26, no. 2, pp. 211-243, 1964. [http://dx.doi.org/10.1111/j.2517-6161.1964.tb00553.x]

[39] J.O. Wobbrock, L. Findlater, D. Gergle, and J.J. Higgins, "The aligned rank transform for nonparametric factorial analyses using only ANOVA procedures", *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)* Vancouver, BC, Canada, 07 May 2011, pp. 143–146. [http://dx.doi.org/10.1145/1978942.1978963]

[40] J. Cohen, "Statistical Power Analysis", *Curr. Dir. Psychol. Sci.,* vol. 1, no. 3, pp. 98-101, 1992. [http://dx.doi.org/10.1111/1467-8721.ep10768783]

[41] J.W. Tukey, "Comparing individual means in the analysis of variance", *Biometrics,* vol. 5, no. 2, pp. 99-114, 1949. [http://dx.doi.org/10.2307/3001913] [PMID: 18151955]

[42] DS Kerby, "The simple difference formula: An approach to teaching nonparametric correlation", *Comprehensive Psychology,* vol. 3, no. 1, 2014. [http://dx.doi.org/10.2466/11.IT.3.1]

[43] "The R project for statistical computing.", Available from:https://www.R-project.org/

[44] R. Lenth, H. Singmann, J. Love, P. Buerkner, and M. Herve, "Estimated marginal means", Available from: https://CRAN.R-project.org/package=emmeans

[45] F.G. Praticò, "Impact of pavement friction decay on speed limits and autonomous vehicles: A theoretical and experimental study", *J. Road Eng.,* vol. 5, no. 1, pp. 35-47, 2025. [http://dx.doi.org/10.1016/j.jreng.2024.09.001]