Issue 25(2), 2025, pp. 1-32
ISSN: 1567-7141
TU Delft OPEN Publishing

EJTIR

Research article
https://ejtir.tudelft.nl
DOI: 10.59490/ejtir.2025.25.2.7557

Incorporating Behavioral Adaptation of Human Drivers in Predicting Traffic Efficiency of Mixed Traffic: A Case Study of Priority T-Intersections

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Keywords
Behavioral adaptation
Mixed traffic
Gap Acceptance
Microscopic Traffic Simulation
Traffic efficiency

Publishing history
Submitted: 19 May 2024
Revised date(s): 28 June 2024
Accepted: 19 February 2025
Published: 08 April 2025

Cite as
Reddy, N., Raju, N., Farah, H., & Hoogendoorn, S. (2025). Incorporating behavioral adaptation of human drivers in predicting traffic efficiency of mixed traffic: A case study of priority T-intersections. *European Journal of Transport and Infrastructure Research, 25*(2), 1-32.

Abstract

As automated vehicles (AVs) become more common, it is important to understand how human-driven vehicles (HDVs) would interact with them. This research investigated HDV gap acceptance behavior in mixed traffic with AVs at a priority intersection, focusing on how mixed traffic factors affect this behavior and overall traffic efficiency.

Using a driving simulator, four scenarios were tested by varying AV driving style (less defensive, more defensive, and HDV-like) and AV recognizability (distinguishable or not from HDVs). Gap acceptance models were estimated based on the collected trajectory data. These models were then integrated into the SUMO microscopic traffic simulation platform, where a T-intersection network was set up. Simulation runs varied based on AV driving style, recognizability, penetration rate (0-75% in 25% increments), and whether HDV behavioral adaptation was considered.

The results indicated increased minor road vehicle delays with higher AV penetration rates. Recognizable less defensive AVs, and more defensive AVs with high penetration rates caused the largest delays for minor road vehicles compared to other conditions. Ignoring behavioral adaptation led to a delay underestimation of up to 75% for minor road vehicles. In conclusion, there is behavioral adaptation in gap acceptance of HDVs in mixed traffic environments. Taking into account the behavioral adaptation is essential for accurately assessing traffic efficiency in mixed traffic conditions, and guiding AV deployment policies.

1 Introduction

It is expected that the presence of Automated Vehicles (AVs) will increase in traffic in the coming decades due to their anticipated benefits to traffic safety, traffic efficiency, and the environment (Greenblatt & Shaheen, 2015; Piao et al., 2016). This will result in a mixed traffic condition, in which human-driven vehicles (HDVs) will interact with AVs in different road situations. Human drivers' behavior could be influenced by the driving styles and the recognizability of AVs, and as a result change their driving behavior (Arvin et al., 2020; Nyholm & Smids, 2020; Reddy et al., 2022). We refer to this change in driving behavior as *behavioral adaptation*, which Kulmala & Rama (2013) define as '*any change of driver, traveler, and travel behaviors that occurs following user interaction with a change to the road traffic system, in addition to those behaviors specifically and immediately targeted by the initiators of the change*'. Therefore, behavioral adaptation could influence the nature of traffic interactions, which in result could influence traffic safety and efficiency. Earlier studies employed microscopic traffic simulation to predict the performance of mixed traffic. However, these studies did not consider possible behavioral adaptation to gain an accurate prediction of the performance of mixed traffic. This will be the main aim of this study.

The following sub-sections first describe findings from earlier studies on the existence of human drivers' behavioral adaptation in mixed traffic followed by works focusing on microscopic simulation of mixed traffic.

1.1 Human drivers' behavioral adaptation in mixed traffic

There is an increasing evidence of HDVs' behavioral adaptation due to interaction with AVs. Both field tests as well as driving simulator studies were conducted to investigate behavioral adaptation.

Several studies used data from controlled field tests or real-life data. For example, Mahdinia et al. (2021) studied in a field test the effect of HDVs following behavior of AVs on traffic safety and environmental impact. They found that HDVs followed AVs with lower speed and acceleration volatility resulting in a more stable traffic flow behavior. They also found that the time-to-collision improved significantly and fuel consumption and emissions reduced when an HDV followed an AV compared to following an HDV. Wen et al. (2022) used real-world naturalistic driving data (Waymo Open Dataset from the United States) that consisted of trajectories of the SAE Level 4 AVs and surrounding vehicles at 10-Hz frequency. They also found that HDVs exhibit lower driving volatility (velocity, acceleration/deceleration) and larger time-to-collision values when following AVs. Moreover, they also found that HDVs adopt shorter time headways when following AVs. Chunxi et al. (2022) used the same dataset to study HDVs interactions with AVs during car-following and car-passing events. They found that drivers kept larger distance gap and time gap when they interacted with AVs as compared to when they interacted with HDVs. However, HDVs had larger standard deviation in speed and smaller time-to-collision when following AVs compared to HDVs which the authors interpret that it is caused by drivers' difficulty to anticipate AVs' speed changes. Wang et al. (2023) also used the same dataset to study HDVs following AVs at signalized intersections. They found that HDVs maintained a shorter standstill distance behind an AV (1.73 m) compared to behind an HDV (2.77 m). The reaction time for HDVs when starting to accelerate behind AVs (0.49 s) was shorter than that behind HDVs (1.04 s). Other field tests investigated the effect of the driving style and recognizability of AVs (Rahmati et al., 2019; Zhao et al., 2020). They focused on HDVs' car following behavioral adaptation and found that human drivers adopt shorter time headways in car-following when following AVs. In their study, Rahmati et al. (2019) adopted a deterministic acceleration model to model AVs; the speed profile of AVs was less volatile than HDVs. Additionally, there was no difference in appearance of the AV and HDV. In the study of Zhao et al. (2020), the appearance of the AV was changed to make it recognizable and non-recognizable when necessary. Soni et al. (2022) executed a controlled field test to investigate the gap acceptance behavior using the Wizard of Oz method (in the AV scenario, the vehicle was recognizable as an AV). They found that human drivers' critical gaps (measured as the last moment the human driver indicated it would still be safe to merge) were significantly smaller when they merged in front of an AV compared to when they merged in front of an HDV. The critical gaps further reduced when drivers were provided with positive information about AVs. Hensch et al. (2023) studied drivers gap acceptance behavior during parking maneuvers in mixed traffic and found effects of factors such as vehicle size, approach speed, and personal driver characteristics; and from the perspective of AVs, they suggested that AVs should offer various driving style profiles that cater to individual driver preferences.

Other studies conducted driving simulator experiments to investigate behavioral adaptation. For example, Stange et al. (2022) executed a driving simulator experiment to investigate the effect of driving in mixed traffic with level 3 AVs on the driving behavior of HDVs. They varied AV penetration rate and appearance of the AVs using external human-machine interfaces (eHMIs). With increasing AV penetration rate, the average speed of HDVs was found to significantly decrease, (in the simulation, AVs had desired speeds closer to the speed limit while HDVs had higher desired speeds) while the percentage of safety critical interactions (<1 s time headway) with AVs as lead vehicles was found to increase, in line with the results of Chunxi et al. (2022). Ma & Zhang (2022) studied drivers' subjective feelings and stated decision-making in mixed traffic by showing people videos of scenarios recorded from a driving simulator. The drivers' driving style was found to affect their subjective feelings and decision-making. Aggressive and moderate drivers felt more anxious and less comfortable in HDV-AV interactions than in HDV-HDV interactions. They also were more likely to take advantage of AVs. While for defensive drivers no difference was found. Other driving simulator studies investigated the effect of the driving style and recognizability of AVs (Fuest et al., 2020; Gouy et al., 2014; Razmi Rad et al., 2021; Schoenmakers et al., 2021). They focused on HDVs' car following behavioral adaptation; Razmi Rad et al. (2021) also investigated lane changing behavior; Fuest et al.(2020) looked at road works, traffic jam situations, and lane changes. In general, they observed that human drivers adopt shorter time headways in car-following when following AVs or when driving alongside AV platoons. Trende et al. (2019) investigated human drivers' gap acceptance at intersections, adopting a driving simulator. They observed that human drivers accepted gaps more frequently in front of recognizable AVs than in front of HDVs. Although AVs and HDVs drove similarly in their study, drivers were provided information that that AVs drove to avoid collisions.

These studies indicate that human driving behavior changes when interacting with AVs in their road environment. While most of these studies focused on understanding the behavioral adaptation of HDVs when interacting with AVs, scaling up of these interactions is needed to understand the effects of such behavioral adaptation on traffic performance. Several studies used microscopic traffic simulation for insights into performance of mixed traffic. We now discuss some of these studies.

1.2 Microscopic simulation studies of mixed traffic

Microscopic simulation studies have investigated traffic efficiency and safety in mixed traffic. Papadoulis et al. (2019) used microscopic traffic simulation (VISSIM) to study the safety impact of connected and automated vehicles (CAVs) on a motorway corridor. In their study, CAVs detected other nearby CAVs and formed platoons of smaller headways than HDVs. They found that the estimated traffic conflicts reduced by 12-47% to 90-94% when the CAV penetration rates increased from 25% to 100%, compared to conventional traffic conditions. Calvert et al. (2017) found that at low penetration levels, AVs had small negative effects on traffic flow and road capacity due to larger car-following time gaps; improvements were seen only at penetration levels above 70%. Olia et al. (2017) found that road capacity was largely insensitive to the penetration rate increase of regular AVs. However, cooperative AVs (i.e., CAVs) significantly increased highway capacity with penetration rates higher than 30%. Schakel et al. (2010) studied the effect of Cooperative Adaptive

Cruise Control (CACC) on traffic flow stability. They found that the duration of shockwaves reduced with increase in CACC penetration rate (0% to 50% and 100%). Ye & Yamamoto (2018) found that up to an AV penetration rate of 30% in microscopic traffic simulation, road capacity increased gradually, and the time headway of AVs had no large effect. Over 30%, the time headway of AV had a crucial impact on the road capacity. Arvin et al. (2020) investigated the safety impacts at intersections in mixed traffic consisting of HDVs, ACC vehicles, and CACC vehicles. They used the number of longitudinal conflicts and driving volatility (velocity and acceleration/deceleration) as safety indicators. They found significant safety improvements when the penetration rate of ACC was above 40%. The average speed and travel time at intersections also improved with increasing ACC/CACC vehicles.

1.3 Summary and research gaps

Most existing studies investigating behavioral adaptation focused on car-following behavior, with some studies also looking at lane-changing behavior. However, there is not yet a good understanding of the effect of recognizability and driving style of AVs on HDVs' driving behavior. Overall, there is evidence that shows that human drivers adopt their driving behavior when they interact with AVs in mixed traffic. Barring a few studies (Soni et al., 2022; Trende et al., 2019), the behavioral adaptation of HDVs in mixed traffic is not yet considerably investigated at intersections. Also, existing microscopic traffic simulation studies that targeted to predict traffic flow efficiency and traffic safety of mixed traffic mainly focused on the effect of AV penetration rate, and vastly model the behavior of human drivers using models that were developed and calibrated for completely human-driven traffic. To our knowledge, to date there has not been a microscopic traffic simulation study to investigate the effect of mixed traffic at priority intersections considering behavioral adaptation in gap acceptance behavior. Therefore, the research gaps can be summarized as follows:

- Current studies on human drivers' behavioral adaptation in mixed traffic focus mainly on the car-following and lane changing behavior, not behavior at intersections.
- Microsimulation studies focus on the effect of AV penetration rate, not on aspects such as AVs recognizability and driving style.
- Microsimulation studies assume no behavioral adaptation in HDV driving behavior.

A previous study (Reddy et al., 2022) focused on studying gap acceptance behavior at priority T-intersections in mixed traffic. Adopting a driving simulator, the effects of AV-related factors such as AVs' driving styles and recognizability on drivers' gap acceptance behavior were investigated. In this study we estimate gap-acceptance models and implement them in a microscopic traffic simulation to study the impacts on traffic efficiency in different future scenarios. We investigate the effects of AV penetration rate, AV driving style, AV recognizability, and the effect of considering versus ignoring behavioral adaptation on traffic efficiency.

2 Research questions and approach

This study focuses on studying gap acceptance behavior at priority T-intersections in mixed traffic. To predict the effects on traffic efficiency, different scenarios were simulated focusing on mixed traffic factors such as AV driving styles, AV recognizability, and AV penetration rates. Therefore, the main research question is*: How does mixed traffic affect the traffic efficiency of priority T-intersections?*

The sub research questions are:

1. What is the effect of AVs' **penetration rate** on the efficiency of mixed traffic at priority T-intersection?

2. What is the effect of AVs' **recognizability** on the efficiency of mixed traffic at priority T-intersection?
3. What is the effect of AVs' **driving style** on the efficiency of mixed traffic at priority T-intersection?
4. What is the effect of **considering human drivers' behavioral adaptation** in mixed traffic in the context of the above questions?

To answer the research questions, we first set-up a driving simulator experiment to study human drivers' gap acceptance behavior at priority T-intersections in mixed traffic (Reddy et al., 2022). Using the data from the driving simulator experiment, in this paper we estimate gap acceptance models to mathematically describe human drivers' interactions with AVs and their gap acceptance behavior. To scale-up these interactions and study the effect of mixed traffic on traffic efficiency, we set-up a simulation network of a T-intersection. We then implement the estimated models in the simulation, and measure traffic efficiency indicators.

The structure of the rest of this paper is as follows. First, we explain in *Section 3* the driving simulator experiment used to collect data of human drivers' gap acceptance behavior in mixed traffic. Then in *Section 4* we present the results of the estimated gap acceptance models using the collected data. In *Section 5* we explain the set-up of the microscopic traffic simulation experiments. Then in *Section 6* we present the results of the simulation experiments and discuss them in the light of the research questions. Then we consider the threats to the validity of the results. Finally, we propose recommendations for policy and future research.

3 Driving simulator experiment

The following section briefly explains the driving simulator experiment set-up, as well as the data collection and processing. A more detailed description of this experiment can be found in our earlier publication Reddy et al. (2022).

3.1 Equipment and promotion

We used the driving simulator located at the Faculty of Civil Engineering of Delft University of Technology in the Netherlands. This driving simulator has a fixed base and three screens of 4K resolution that provide about 180-degree view. It has pedals and a Fanatec steering control wheel. The scenarios were designed using the software SCANeR (v1.9) from AV Simulation.

The Human Resource and Ethics Committee (HREC) of Delft University of Technology provided ethical approval for carrying on the experiment. We recruited the participants by promoting the experiment in printed local newspaper and online social networking platforms. Drivers were required to have a valid driving license to take part in the experiment. The duration of the experiment per participant was between 60 to 90 minutes. This included a pre-experiment questionnaire, briefing about the experiment, a practice drive (to get familiar with the driving simulator), the experiment scenarios, adequate breaks between scenarios, and post-experiment questionnaires. Each participant was compensated with a 15€ voucher at the end of the experiment. One hundred and fourteen participants took part in the experiment.

3.2 Route

The route (depicted in Figure 1) that the participants drove on consisted of motorway driving, regional road driving, and non-signalised T-intersections with priority. The speed limits were 100 km/h on the motorway, 80 km/h on the regional road, and 50 km/h on the urban road. This paper focuses on the three T-intersections. Before each intersection, a stop sign on the minor road made sure that drivers stopped completely before proceeding to enter the intersection. Positioning the intersections after the motorway and regional road sections ensured that drivers sufficiently experienced the traffic condition of that scenario beforehand.

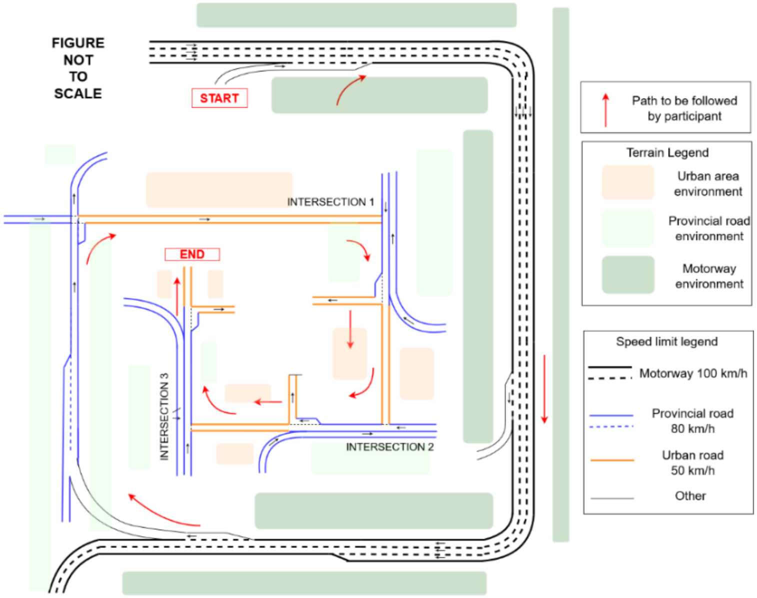

Figure 1. A sketch of the route in the driving simulator (Reddy et al., 2022).

3.3 *Experiment design*

Scenarios in the experiment differed in the AVs' recognizability and their driving styles. Each participant experienced four scenarios. Table 1 shows a description of the scenarios.

Table 1. Description of Scenarios

Number	Vehicle types	Were AVs Recognizable?	AVs' Driving style
1	Only HDVs	-	-
2	HDVs & AVs	Not recognizable (NR)	AV
3	HDVs & AVs	Recognizable (R)	AV
4	HDVs & AVs	Recognizable (R)	HDV

Groups of participants were made to experience different AV driving styles. Participants were divided into three groups which reflect the AV driving style scenario they experienced: *More defensive* AVs, *Less defensive* AVs, and *Mixed* AVs. Drivers in the group of *More defensive/ Less defensive* AVs only experienced AVs of the respective driving style in mixed traffic. The *Mixed* AVs scenario had *More defensive* and *Less defensive* AVs in a 3:2 proportion. This paper focuses on the *Less defensive* and *More defensive* AVs groups only as the same participants did not experience the three different traffic conditions (i.e., *More defensive, less defensive, and Mixed* AVs). All the scenarios had a 50% AV penetration rate.

The driving behavior of AVs and HDVs are described in Table 2. The target time gaps when car following of AVs were chosen from publicly accessible information about ACC settings of commercial vehicles (Makridis et al., 2021; Raju et al., 2022). The target car-following time gaps for HDVs were decided from earlier studies (Taieb-Maimon & Shinar, 2016, Winkelbauer et al., 2019). As we expect that AVs would not exceed legal speed limits, their desired speeds were set to the speed limit. We were unable to change other parameters such as maximum acceleration/ deceleration or lane changing behaviors in the driving simulator.

Table 2. Driving behaviors of HDVs and AVs

Vehicle type	Target speed (desired)	Target following gap (s) (time gap when car following)
HDV	Randomly drawn between a factor 0.9 and 1.1 of the speed limit	Min 0.5 s; Max 1.5 s; Distribution: negative exponential (truncated)
More defensive AV	Equal to the speed limit	3.5 s
Less defensive AV	Equal to the speed limit	1.5 s
Mixed AV	A mix of *More defensive* and *Less defensive* AVs in a 3:2 proportion	

The gaps between vehicles on the major road at the intersections were randomly drawn from a uniform distribution between 3 and 10 seconds so that the gaps available were neither very small nor very large (Beanland et al., 2013). All vehicles on the major road had gaps from this distribution, even if the vehicles were *Less defensive* or *More defensive* AVs. This was to ensure a fair comparison because the gap size significantly influences the acceptance or rejection of a gap (Beanland et al., 2013). Consequently, the effects of the recognizability of AVs and that of the driving style of AVs were separated.

Appearance of the AVs was therefore the only distinction between AVs and HDVs on the major road in scenarios where the AVs were set to be recognizable (i.e., distinguishable from HDVs), they were yellow in color. The participants were shown the appearance of AVs in the driving simulator prior to the start of their drive. Hence, they could identify and distinguish the recognizable AVs from other HDVs. No other explicit information on AVs' driving style was provided to the drivers. Both, *More defensive* and *Less defensive* AVs, had the same appearance when they were recognizable. Before approaching the intersections, drivers passed through the motorway and the regional road. The type of traffic that the participants interacted with in these earlier sections was expected to affect their resulting gap acceptance behavior, therefore being a "carry-over" effect (Reddy et al., 2022). In the 1st and 2nd scenarios, all vehicles had the appearance of HDVs, which includes the major road vehicles at the intersections. In the 3rd and 4th scenarios, half of the vehicles in traffic appeared as AVs. Therefore, 50% of the major road vehicles were recognizable as AVs. However, the gaps between all the major road vehicles in all scenarios were drawn from the same uniform distribution as specified before. Each scenario lasted between 10 and 12 minutes on average. In between scenarios, sufficient breaks were provided to the participants. The order of the scenarios was randomized to counter any learning effect.

3.4 Collection and Processing of Data

The data consisted of the following: the simulator timestamp, speed, acceleration, and position (x, y, z) for all vehicles within that scenario. These data were collected at 20 Hz frequency and then converted to 4 Hz (4 data points per second) to decrease processing time. Twelve participants out of the 114 experienced severe nausea and/or did not finish the experiment. Also, 7 participants behaved erroneously at the T-intersections (did not follow instructions) or drove abnormally. These drivers were excluded from the dataset. The final dataset of gap acceptance had 95 participants. Seventy- one of them were males, and 24 females. Thirty-eight participants were Younger (18-29 years), 27 were Middle aged (30-54 years), 25 were Older (55+ years), and 5 of Unknown age.

4 Gap acceptance modelling and estimation

4.1 Modelling approach

Gap acceptance is a binomial process wherein for every offered gap, a driver decides on accepting or rejecting the gap. We adopted a *generalized linear model* (logistic regression) because the predicted variable was binomial (we predicted the probability that a driver accepts a gap), while the explanatory variables could be continuous and/or categorical (Dutta & Ahmed, 2018; Zohdy et al., 2010). To model gap acceptance behavior, we estimated three models using R (RStudio Team, 2022) that predict the probability of accepting an offered gap, using maximum likelihood estimation method. The first model (Model 1: conventional traffic) was the gap acceptance model for HDVs only traffic. For this, observations from scenario 1 (only HDVs) in Table 1 were used. The second model (Model 2: *Less defensive* AV traffic) was the gap acceptance model of drivers when driving in traffic with *Less defensive* AVs. The observations from scenarios 2 and 3 in Table 1 from the drivers of the *Less defensive* group were used to estimate this model. The third model (Model 3: *More defensive* AV traffic) was the gap acceptance model of human drivers when driving in mixed traffic with *More defensive* AVs. The observations from scenarios 2 and 3 in Table 1 from the drivers of the *More defensive* group were used to estimate this model. As the drivers in the *Less defensive* and *More defensive* groups were different (mutually exclusive), it was possible to estimate two separate models for *Less defensive* and *More defensive* AV traffic. Table 3 presents the variables that were used for the gap acceptance models. We used the AIC (Akaike Information Criterion), which considers both the predictive power and the frugality (using fewer variables) of the model, to test the statistical performance of the models. The model that performed best on AIC was selected.

Table 3. Description of the variables in the estimated gap acceptance models

Model variable	Description
Gap	The size of the gap on the major road offered to the minor road vehicle. It is the time gap (in seconds) between two consecutive vehicles on the major road.
Driving style of human driver	The driving style of the human driver (Anxious and dissociative, Careful and distress reducing, or Risky and aggressive) derived from the self-reported driving behavior questionnaire (Taubman-Ben-Ari et al., 2004)
Scenario order	The order of the scenario (1, 2, 3, or 4) that the participants encountered in the experiment
Appearance of follower	The appearance of the follower vehicle (i.e., AV or HDV) on the major road when the minor road vehicle accepted an offered gap.

4.2 Modelling results

Tables 4, 5, and 6 present the coefficient estimates for Model 1 (*Conventional traffic*), Model 2 (*Less defensive* AV traffic), and Model 3 (*More defensive* AV traffic), respectively. All the models can be represented by the following equations:

$$p = \frac{e^{U(x)}}{1 + e^{U(x)}} \quad [1]$$

$$U(x) \sim Intercept + \sum_{i=1}^{N} \beta_i \cdot x_i + \varepsilon \quad [2]$$

Where p indicates the probability to accept a gap, x indicates the vector of explanatory variables, $U(x)$ indicates the utility function, β indicates the row of coefficient parameters for the respective explanatory variables, ε indicates the error term, and N indicates the number of explanatory variables.

Table 4. Estimated coefficients of the generalized linear logistic model for gap acceptance in conventional traffic (Model 1: *Conventional traffic*)

Coefficients	Estimate	Standard error	z-value	Pr (>z)
(Intercept)	-5.35	0.58	-9.22	< 0.001
Gap	0.62	0.07	8.79	< 0.001
Driving style of human driver (Ref.: Anxious and dissociative)				
Careful and distress reducing	0.64	0.29	2.18	0.029
Risky and aggressive	0.62	0.34	1.84	0.065
Order of encountering the scenario (Ref.: Scenario order 1)				
Scenario order 2	0.37	0.33	1.12	0.264
Scenario order 3	0.57	0.31	1.81	0.069
Scenario order 4	0.52	0.38	1.39	0.160
AIC	436.30			

Table 5. Estimated coefficients of the generalized linear logistic model for gap acceptance in mixed traffic with less defensive AVs (Model 2: *Less defensive* AV traffic)

Coefficients	Estimate	Standard error	z-value	Pr (>z)
(Intercept)	-6.88	1.23	-5.59	<0.001
Gap	0.85	0.16	5.30	<0.001
Driving style of human driver (Ref.: *Anxious and dissociative*)				
Careful and distress reducing	0.31	0.29	1.06	0.289
Risky and aggressive	0.21	0.32	0.65	0.510
Appearance of the follower (Ref.: *AV App (AV), Foll App (AV)*)				
AV App (AV), Foll App (HDV)	2.76	1.48	1.86	0.063
AV App (HDV), Foll App (HDV)	1.29	1.38	0.94	0.350
Interaction term (Ref.: Gap & AV App (AV), Foll App (AV))				
Gap & AV App (AV), Foll App (HDV)	-0.40	0.21	-1.93	0.054
Gap & AV App (HDV), Foll App (HDV)	-0.14	0.19	-0.72	0.470
Order of encountering the scenario (Ref.: *Scenario order 1*)				
Scenario order 2	0.44	0.34	1.29	0.194
Scenario order 3	0.20	0.33	0.61	0.540
Scenario order 4	0.65	0.37	1.77	0.077
AIC	443.15			

Table 6. Estimated coefficients of the generalized linear logistic model for gap acceptance in mixed traffic with more defensive AVs (Model 3: *More defensive* AV traffic)

Coefficients	Estimate	Standard error	z-value	Pr (>z)
(Intercept)	-4.83	0.50	-9.58	< 0.001
Gap	0.64	0.07	8.63	< 0.001
AIC	409.64			

4.3 Insights from the models

It can be observed from the gap acceptance model for the conventional traffic (Table 4) that the gap size has a very significant effect on gap acceptance, drivers have higher probability to accept larger gaps. Furthermore, drivers with careful and distress reducing driving style tend to accept larger gaps compared to drivers with anxious and dissociative driving style, while those with a risky and aggressive driving style did not differ significantly (at the 95% confidence level) in their gap acceptance tendency from those with anxious and dissociative driving style. The scenario order was not found to significantly affect the gap-acceptance probability, although at a 90% confidence level, gaps offered in Scenario order 3 tended to have a greater probability of being accepted compared to gaps offered in Scenario order 1. For the gap acceptance probability with *Less defensive* AV traffic (Table 5), the gap size again has the greatest influence on the probability to accept the gap. Also, in traffic having recognizable AVs, drivers have higher probability to accept gaps in front of HDVs compared to in front of recognizable *Less defensive* AVs (at a 90% confidence level). The scenario order was again not found to significantly affect the gap-acceptance probability, although at a 90% confidence level, gaps offered in Scenario order 4 tended to have a greater probability of being accepted compared to gaps offered in Scenario order 1. The driving styles of human drivers were not found to significantly affect the gap acceptance in this scenario. For the gap acceptance probability with *More defensive* AV traffic (Table 6), in terms of the best performing model, the gap size was found to be the only variable determining the probability of gap acceptance. Larger gaps resulted in a greater probability of them being accepted.

5 Microscopic traffic simulation set-up

The estimated models were then implemented in microscopic traffic simulation. This section explains the configuration of the microscopic traffic simulation which includes the road network, vehicle types and driving behaviors. We used the SUMO simulation platform (Lopez et al., 2018) for this research as it is open-source, well documented and provides the possibility to program the behavioral models using TraCI (The **Tra**ffic **C**ontrol **I**nterface). In which, the TraCI script controls the gap acceptance behavior of the minor road vehicles entering the intersection based on the implemented gap-acceptance behavioral models. To capture the variability, simulation runs were carried out for 10 different seeds for each of the simulation scenarios. For a better understanding of the simulation set-up, the entire simulation process is detailed in Appendix A, in Figure A-1 which describes the TRACI python script, the simulation set-up and data outcome.

5.1 Network

The designed road network (Figure 2) is a simple priority T-intersection, with a major road and a minor road approaching each other at the intersection node, and the major road continuing straight to depart from the intersection node. Vehicles on the minor road are expected to stop and allow priority to major road vehicles. All the roads were single lane roads. The length of the major road approach leg was 670 m, that of the major road departure leg was 540 m, and that of the minor road was 360 m. Vehicles were generated at different desired speeds as will be explained further below. We designed a single T-intersection and not a network of connected T-intersections because the estimated gap acceptance models were applicable for human drivers only. A connected network of T-intersections on which mixed traffic is operating would require in addition defining how AVs conduct gap acceptance, which is out of the scope of this paper. However, the results at the single T-intersection are sufficient to illustrate the effect that mixed traffic has on traffic performance of a single T-intersection.

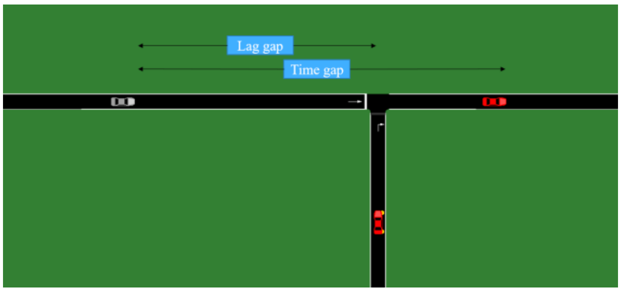

Figure 2. T-intersection in SUMO with a vehicle on the minor road and two vehicles on the major road.

5.2 Vehicle types and attributes

Major road: Traffic on the major road consisted of both HDVs and AVs. Table 7 describes their attributes. The traffic volume on the major road was chosen such that it results in a gap distribution so that the vehicles on the minor road have reasonable opportunity to merge, at the same time hindered to a certain extent by traffic on the major road. This was fixed at 600 vehicles per hour. Gaps between vehicles on the major road were generated using a Poisson distribution. Figure 3 presents the headways distribution of generated vehicles on the major road. The total traffic volume and the distribution of generated headways on the major road remained the same irrespective of any simulation condition. Generated HDVs had a distribution of desired time gaps drawn randomly from [0.5 s, 0.75 s, 1 s, 1.25 s, 1.5 s] to result in a distribution shown in Figure 4, which presents the volume distribution of HDVs with different desired time gaps on the major road at different AV penetration rates. The desired time gaps refer to the distances with the preceding vehicle when car-following. This is different from the critical gaps, which is during gap acceptance. All vehicles followed the Intelligent Driver Model (IDM) (Treiber et al., 2000) with the parameters stated in Table 7 (additionally, the following parameters were used: Delta = 4, Tau = 0.5 s, Acceleration = 2.6 m/s^2). Equations 3 and 4 represent the IDM.

$$\dot{v}_\alpha = a^{(\alpha)}\left[1-\left(\frac{v_\alpha}{v_0^{(\alpha)}}\right)^\delta-\left(\frac{s^*(v_\alpha,\Delta v_\alpha)}{s_\alpha}\right)^2\right] \quad [3]$$

$$s^*(v,\Delta v) = s_0^{(\alpha)} + s_1^{(\alpha)}\sqrt{\frac{v}{v_0^{(\alpha)}}} + T^\alpha v + \frac{v\Delta v}{2\sqrt{a^{(\alpha)}b^{(\alpha)}}} \quad [4]$$

Where $\dot{v}_\alpha$is the acceleration, $a^{(\alpha)}$is the maximum acceleration, $v_\alpha$is the velocity, $v_0^{(\alpha)}$ is the desired velocity, δ is the acceleration exponent, $s^*(v_\alpha,\Delta v_\alpha)$ is the desired minimum gap, $s_\alpha$is the actual gap, $s_0^{(\alpha)}$ and $s_1^{(\alpha)}$is the jam distance, v is the velocity, T^α is the safe time headway, Δv is the velocity difference, $b^{(\alpha)}$ is the desired deceleration.

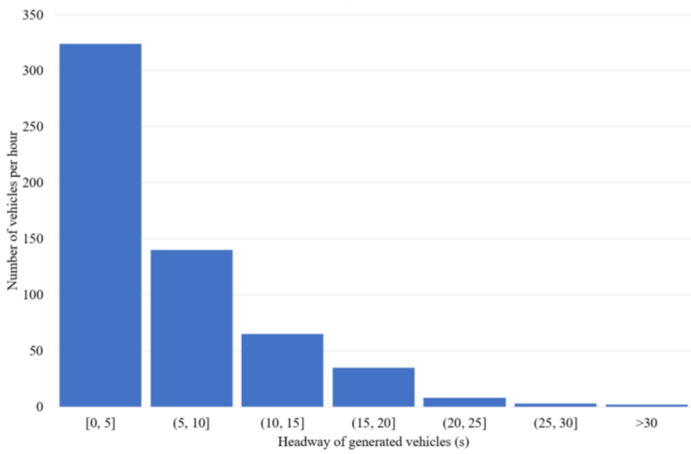

Figure 3. Headway distribution of all vehicles generated on the major road.

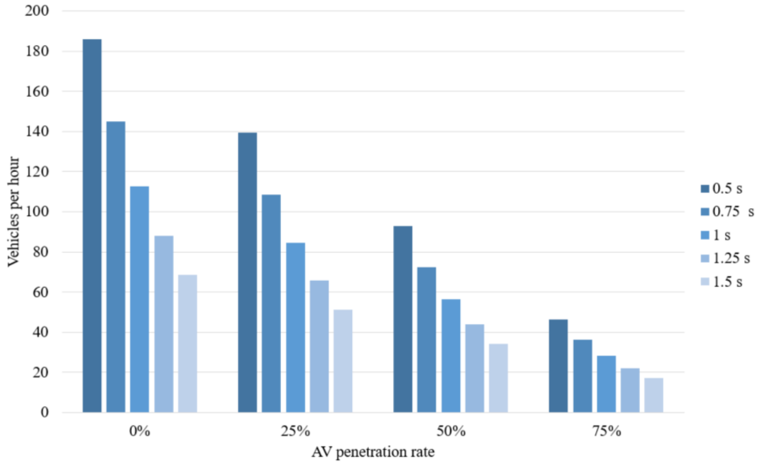

Figure 4. Major road volume distribution of HDVs with different desired time headways at different AV penetration rates.

Table 7. Attributes of vehicles on the major road

Description	Vehicle appearance	Target speed	Desired time gap
HDV	HDV	Randomly drawn between a factor 0.9 and 1.1 of the speed limit (normal distribution)	Drawn from [0.5 s, 0.75 s, 1 s, 1.25 s, 1.5 s]
AVs driving like HDVs	AV	Randomly drawn between a factor 0.9 and 1.1 of the speed limit (normal distribution)	Drawn from [0.5 s, 0.75 s, 1 s, 1.25 s, 1.5 s]
Less defensive AVs	AV	Speed limit	1.5 s
More defensive AVs	AV	Speed limit	3.5 s
Less defensive AVs appearing as HDVs	HDV	Speed limit	1.5 s
More defensive AVs appearing as HDVs	HDV	Speed limit	3.5 s

Minor road: Traffic on the minor road always consisted of HDVs. Each of these HDVs was assigned one of the three Driving styles (Careful and distress-reducing, Anxious and dissociative, and Risky and aggressive), in equal proportion. The driving style assigned to the HDVs only played a role in the gap acceptance behavior models. The vehicles followed the Intelligent Driver Model (IDM) (Treiber et al., 2000) with the target speed randomly drawn between a factor 0.9 and 1.1 of the speed limit (normal distribution), and the desired time gap drawn from [0.5 s, 0.75 s, 1 s, 1.25 s, 1.5 s]. Additionally, the following parameters were used: Delta = 4, Tau = 0.5 s, Acceleration = 2.6 m/s^2. Their gap acceptance behavior was as per the estimated models (Tables 3-5). The traffic volume on the minor road was fixed to one third of the traffic volume of the major road, but only consisted of HDVs.

5.3 *Simulation conditions*

Different simulation conditions were defined based on AV Penetration Rate, AV Driving style (i.e., *Less defensive* and *More defensive*), and AV recognizability. Table 8 presents these variables with their defined levels. Additionally, consideration of behavioral adaptation was also incorporated in these conditions.

Table 8. Design parameters' specifications for simulation set-up

Variables	Levels
Traffic volume on major road	600 veh/h (fixed)
Traffic volume on minor road	200 veh/h (fixed)
AV Penetration Rate	0%, 25%, 50%, 75%
AV Driving style	More defensive, Less defensive
AV recognizability	Recognizable (R), Not Recognizable (NR)
BA consideration	BA considered (BA), BA not considered (NoBA)

The simulation conditions were based on different combinations of the levels of these variables resulting in a total of 16 unique simulation conditions as presented in Table 9.

Table 9. Simulation conditions definitions

Condition number	Code MPR_DS_R_BA*	AV Market Penetration Rate (MPR)	AV driving style	AV recognizability	Behavioral Adaptation
1	Conventional	-	-	-	-
2	25_LD_NoBA	25%	Less defensive	Not recognizable - (NR)	Without Behavioral Adaptation (NoBA)
3	25_MD_NoBA		More defensive		
4	50_ LD _NoBA	50%	Less defensive		
5	50_ MD _NoBA		More defensive		
6	75_ LD _NoBA	75%	Less defensive		
7	75_ MD _NoBA		More defensive		
8	25_ LD _NR_BA	25%	Less defensive	Not recognizable (NR)	With Behavioral Adaptation (BA)
9	25_ LD _R_BA		Less defensive	Recognizable (R)	
10	25_ MD _BA		More defensive	Recognizable (R)	
11	50_ LD _NR_BA	50%	Less defensive	Not recognizable	
12	50_ LD _R_BA		Less defensive	Recognizable (R)	
13	50_ MD _BA		More defensive	Recognizable (R)	
14	75_ LD _NR_BA	75%	Less defensive	Not recognizable	
15	75_ LD _R_BA		Less defensive	Recognizable (R)	
16	75_ MD _BA		More defensive	Recognizable (R)	

* MPR – Market Penetration Rate; DS – Driving Style; R – Recognizability; NR – Not Recognizable; BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; LD – less defensive; MD – more defensive

5.4 Performance indicators

To evaluate the traffic efficiency, four performance indicators were used:

- Delay per vehicle on the minor road (delay measured as the difference between the predicted and the actual travel time): The delay per vehicle is automatically computed by SUMO and directly available to be measured. The predicted travel time assumes zero waiting time at the intersection and uses the defined speed limit of the road sections and an acceleration and deceleration behavior. The actual travel time for each vehicle is measured and the difference is recorded as the delay for that vehicle. This is done for every vehicle on the minor road.
- Delay per HDV on the major road: The delay per vehicle is automatically computed by SUMO and directly available to be measured. The predicted travel time assumes free flow speed and uses the defined speed limit of the road section. The actual travel time for each vehicle is measured and the difference is recorded as the delay for that vehicle. This is done

for every vehicle on the major road. We separate the delays for the HDVs and AVs based on their predefined IDs that allows us to classify them as HDV or AV.

- Delay per AV on the major road: The method of measurement is the same as the previous indicator.
- Length of the queue on the minor road at the end of the simulation run (expressed in number of vehicles): This is measured by checking the remaining vehicles on the minor road when the simulation period (of 1 hour) is completed. This provides an indication of the queue length built on the minor road, and allows for a fair comparison between different simulation conditions.

Each simulation condition was run with 10 different seeds, and the results were averaged per condition. Every simulation run lasted for a duration of 1 hour. Every simulation run lasted for a duration of 1 hour. There was no cool down period, as we were interested in the difference between the scenarios and not the absolute indicator values.

6 Results

The results have the following structure: firstly, we present the results of delay for minor road vehicles; then we present the results of delay for major road vehicles; finally, the results of the queue length on the minor road. For presenting the delay results, we first show a boxplot of the delay per vehicle containing all simulation conditions. These are followed by tables that display the percentage changes in delays between different conditions, organized by the defined research questions. Then, we also present some boxplots for a subset of the conditions focusing on some interesting observations.

6.1 *Minor road delay*

Figure 5 presents boxplot distributions of the delay per vehicle on the minor road for the different conditions. There are noticeable differences between some conditions, indicating that there may be significant effects of penetration rate, driving style, recognizability, and consideration of behavioral adaptation. For example, in general there appears to be an increase in delay with increasing penetration rates. Also, there appear to be differences between the same condition, but with and without considering behavioral adaptation. Table 10 presents the percentage change in median delay between the different conditions, organized by the research questions.

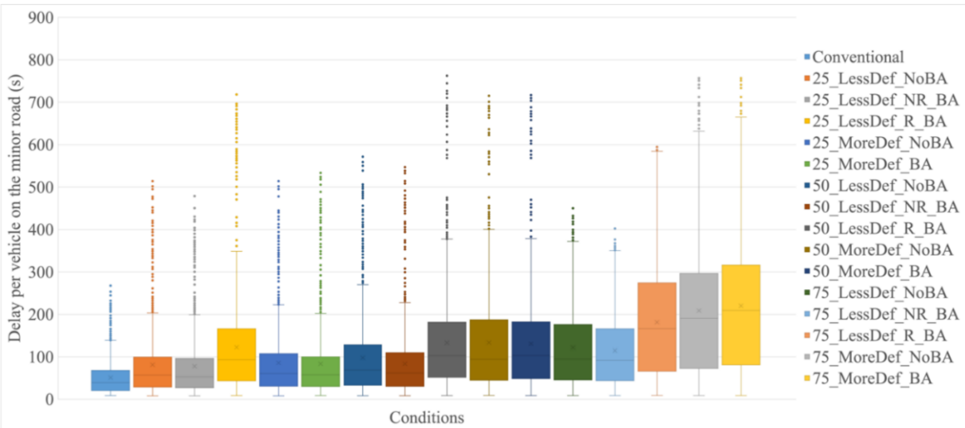

Figure 5. Boxplot distribution of delay per vehicle on the minor road for all conditions (R – Recognizable; NR – Not Recognizable; BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

Studying Table 10 reveals that increasing penetration rates of AVs results in an increase in delay for minor road vehicles, particularly so when AVs have *More defensive* driving style. Also, interesting to note that when human drivers' behavioral adaptation is considered, the increase in delay for minor road vehicles when MPR of recognizable *Less defensive* AVs increases from 50% to 75% is much larger (62.49%), compared to the increase in delay (10.04%) when MPR increases from 25% to 50%. Also, the recognizability of *Less defensive* AVs results in a clear increase in delay compared to when these vehicles are not recognizable, at all penetration rates. An interesting observation is the effect of AV driving style. At low MPR of 25% and when behavioral adaptation is considered the *More defensive* AVs condition results in less delay (-38.28%) for minor road vehicles compared to the recognizable *Less defensive* AVs condition. However, at high MPR of 75% the comparison results in an opposite trend with *More defensive* AVs condition resulting in higher delays for the minor road vehicles (+25.68%) compared to the recognizable *Less defensive* AVs. . This best demonstrates the interplay between the effect of the gap acceptance model and the effect of the major road gaps distribution.

Table 10. Percentage change in median delay between different conditions for vehicles on the minor road

	Condition	Change in median delay per vehicle	
		MPR from	MPR from 50% to 75%
Effect of Market Penetration Rate (MPR)	NoBA, More defensive AVs	+54.97%	+103.17%
	NoBA, Less defensive AVs	+20.39%	+38.15%
	BA, More defensive AVs	+79.44%	+102.92%
	BA, NR Less defensive AVs	+17%	+48.29%
	BA, R Less defensive AVs	+10.04%	+62.49%
	R versus NR *Less defensive* AVs		
Effect of recognizability	BA, MPR 25%		+76.29%
	BA, MPR 50%		+65.79%
	BA, MPR 75%		+81.67%
	More defensive versus Less defensive AVs		
Effect of AV driving style	NoBA, MPR 25%		+6.29%
	NoBA, MPR 50%		+36.83%
	NoBA, MPR 75%		+101.23%
	More defensive AVs versus NR *Less defensive* AVs		
	BA, MPR 25%		+8.80%
	BA, MPR 50%		+66.86%
	BA, MPR 75%		+128.33%
	More defensive AVs versus R *Less defensive* AVs		
	BA, MPR 25%		-38.28%
	BA, MPR 50%		+0.64%
	BA, MPR 75%		+25.68%
	With Behavioral Adaptation versus Without Behavioral Adaptation		
Effect of considering behavioral adaptation (BA)	More defensive AVs MPR 25%		-5.19%
	More defensive AVs MPR 50%		+9.77%
	More defensive AVs MPR 75%		+9.64%
	NR *Less defensive* AVs MPR 25%		-7.38%
	NR *Less defensive* AVs MPR 50%		-9.98%
	NR *Less defensive* AVs MPR 75%		-3.37%
	R *Less defensive* AVs MPR 25%		+63.28%
	R *Less defensive* AVs MPR 50%		+49.24%
	R *Less defensive* AVs MPR 75%		+75.54%

BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; MPR – Market Penetration Rate; MD – *More defensive*; LD – *Less defensive*; R – Recognizable; NR – Not-Recognizable

Boxplots for subsets of conditions are presented next for a better perspective. Figure 6 presents the effects of AV penetration rate and whether behavioral adaptation is considered or not on the delay per vehicle on the minor road **when AVs are more defensive**. In general, as the penetration rate of *More defensive* AVs increases, the delay for the minor road vehicles also increases. This is observed both when behavioral adaptation is considered and when it is not considered. Additionally, for the same penetration rate, there appears to be no significant difference in the delay between when behavioral adaptation is considered compared to when it is not. It may be recalled that recognizability did not play a role in affecting gap acceptance when AVs were *More defensive*.

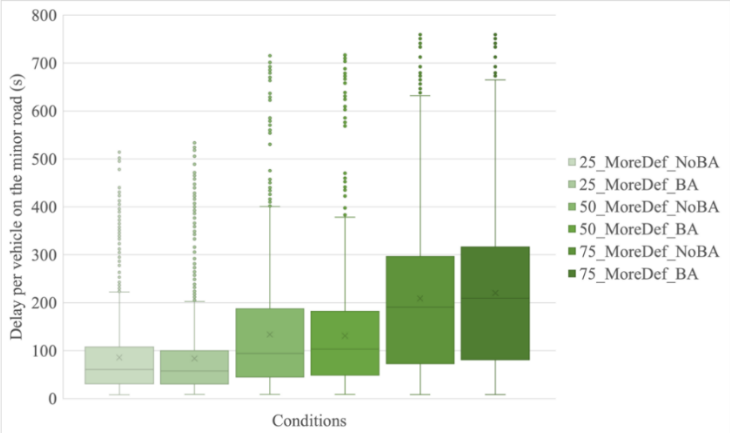

Figure 6. Boxplot of delay per vehicle on the minor road for More defensive AVs, with and without BA consideration, and for different penetration rates (BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; Def – More defensive).

Figure 7 presents the effects of AV penetration rate and AV recognizability on the delay per vehicle on the minor road when **AVs are *Less defensive* and behavioral adaptation is considered**. An increase in penetration rate of *Less defensive* AVs appears to result in an increase in delay both when the *Less defensive* AVs are recognizable and non-recognizable. At all penetration rates, the delay for the minor road vehicles is larger when the *Less defensive* AVs are recognizable compared to when they are non-recognizable.

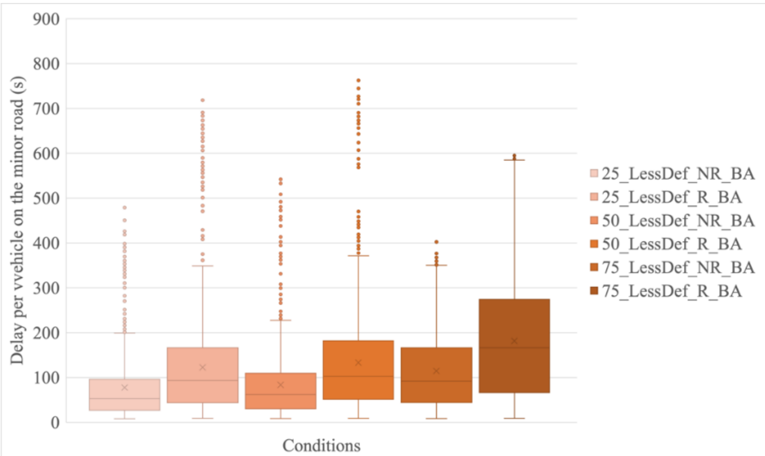

Figure 7. Boxplot of delay per vehicle on the minor road for Less defensive AVs condition and when considering behavioral adaptation, for recognizable vs not-recognizable AVs, and for different penetration rates (R – Recognizable; NR – Not Recognizable; BA – With Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

Figure 8 presents the effects of AV penetration rate and whether behavioral adaptation is considered or not on the delay per vehicle on the minor road, when **AVs are *Less defensive* and not-recognizable** (Note: when behavioral adaptation is not considered, there is no impact if the vehicle is recognizable or not). Again, an increase in penetration rate leads to an increase in delay of minor road vehicle. This is the case both when behavioral adaptation is considered and when it is not considered. At the same penetration rate, the change in delay between when behavioral adaptation is considered and when it is not considered does not seem to be very large (when *Less defensive* AVs are non-recognizable).

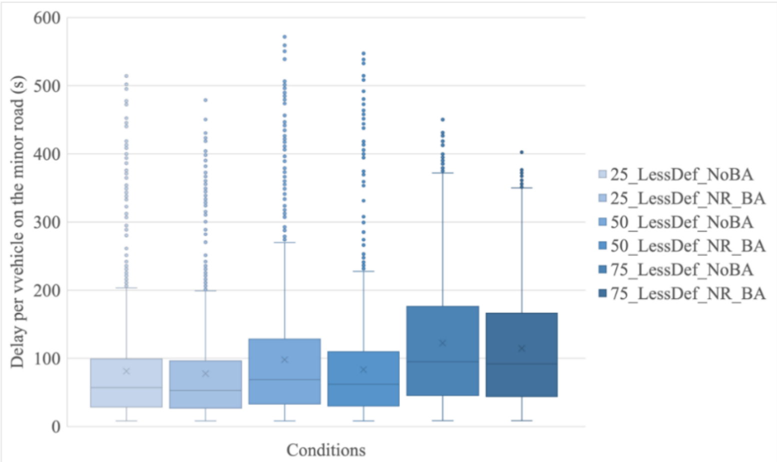

Figure 8. Boxplot of delay per vehicle on minor road for Less defensive AVs, with and without behavioral adaptation consideration when they are not-recognizable, and for different penetration rates (NR – Not Recognizable; BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

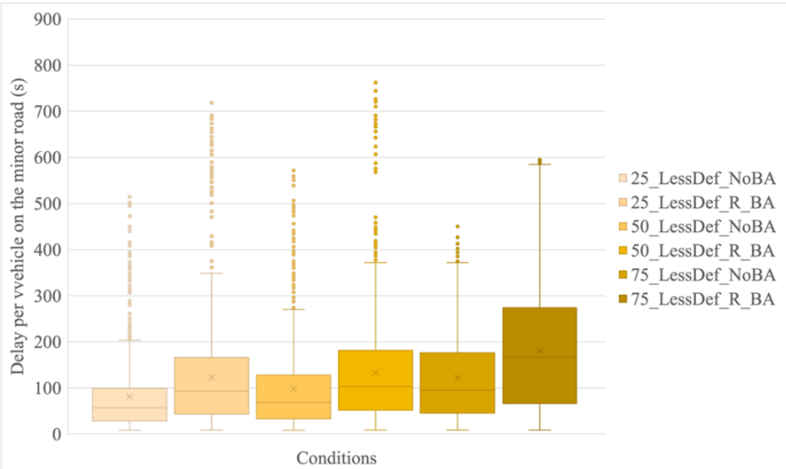

Figure 9. Boxplot of delay per vehicle on minor road for Less defensive AVs, with and without BA consideration when they are recognizable, and for different penetration rates (R – Recognizable; BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

Figure 9 presents the effects of AV penetration rate and whether behavioral adaptation is considered or not on the total delay per vehicle on the minor road, when **AVs are *Less defensive* and recognizable**. Again, an increase in penetration rate of *Less defensive* and recognizable AVs leads to an increase in delay. This is the case both when behavioral adaptation is considered and when it is not considered. At the same penetration rate, the difference in delay between when behavioral adaptation is considered and when it is not considered seems noticeable (when *Less defensive* AVs are recognizable). That is, the delay seems to be larger when *Less defensive* AVs are recognizable and behavioral adaptation is considered.

6.2 Major road delay

Figure 10 presents the boxplot distribution of the delay per vehicle on the major road for AVs only. The effects of AV penetration rate, whether behavioral adaptation is considered or not, AV recognizability, and AV driving style can be observed. The magnitude of the delays compared to the minor road delays is much smaller. This is expected as vehicles on the major road have priority over vehicles on the minor road. From the boxplots, it appears that there are some differences in delays between different conditions.

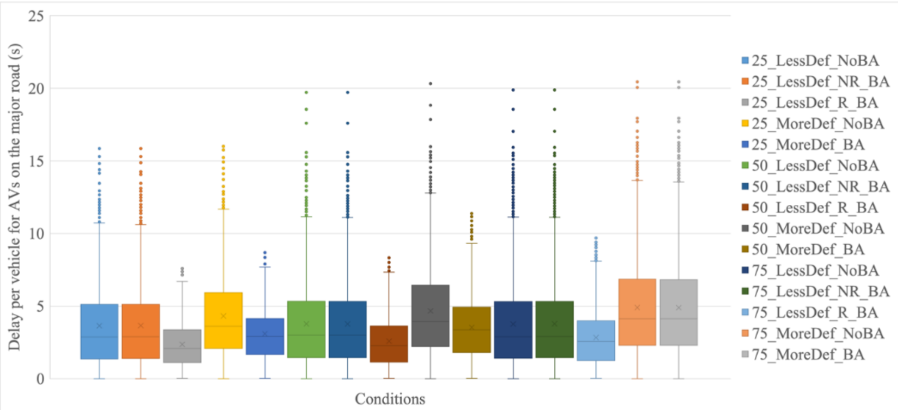

Figure 10. Boxplots of delay per vehicle for AVs on the major road (R – Recognizable; NR – Not Recognizable; BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

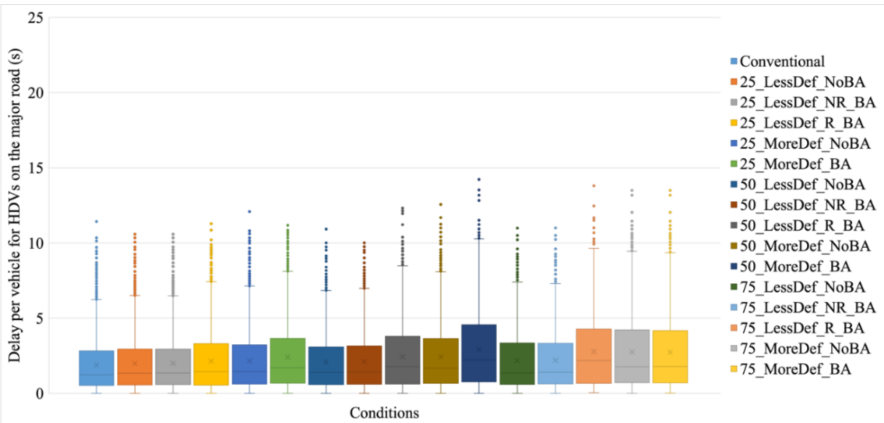

Figure 11. Boxplots of delay per vehicle for HDVs on the major road (R – Recognizable; NR – Not Recognizable; BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

Figure 11 presents the boxplot distribution of the delay per vehicle on the major road for HDVs only. A clear contrast with AVs (Figure 10) is that the delays do not seem to vary much between the different scenarios. Also, the magnitude of delays for HDVs seem to be smaller than the delays for AVs. The median delay in all scenarios is approximately between 1 and 2 seconds, thus not very high (although for large traffic volumes over a longer period of time, it could be meaningful). Therefore, it appears that it is mainly AVs that experience changes in delays on the major road and are delayed by a larger magnitude than HDVs.

Table 11 presents the percentage change in median delay for AVs and HDVs on the major road between the different simulation conditions.

Table 11. Percentage change in median delay between different conditions for AVs and HDVs on the major road

	Condition	Change in median delay per vehicle (percentage)			
		MPR from 25% to 50%		MPR from 50% to 75%	
		AVs	HDVs	AVs	HDVs
Effect of Market Penetration Rate (MPR)	No BA, More Defensive AVs	+9.14%	+15.07%	+4.57%	+5.95%
	BA, Less Defensive AVs	+4.17%	+2.96%	-3.50%	-2.16%
	BA, More Defensive AVs	+15.07%	+30.59%	+22.62%	-19.37%
	BA, NR Less Defensive AVs	+3.81%	+4.80%	-3%	-1.41%
	BA, R Less Defensive AVs	+9.13%	+22.76%	+12.78%	+23.03%
		R versus NR *Less defensive* AVs			
		AVs		HDVs	
Effect of recognizability	BA, MPR 25%	-28.03%		+7.01%	
	BA, MPR 50%	-24.33%		+25.35%	
	BA, MPR 75%	-12.03%		+56.43%	
		More defensive AVs versus *Less defensive* AVs			
		AVs		HDVs	
Effect of AV driving style	No BA, MPR 25%	+25.35%		+8.15%	
	No BA, MPR 50%	+31.33%		+20.86%	
	No BA, MPR 75%	+42.31%		+30.88%	
		More defensive AVs versus NR *Less defensive* AVs			
		AVs		HDVs	
	BA, MPR 25%	+1.04%		+25.46%	
	BA, MPR 50%	+12%		+56.34%	
	BA, MPR 75%	+41.58%		+27.86%	
		More defensive AVs versus R *Less defensive* AVs			
		AVs		HDVs	
	BA, MPR 25%	+40.38%		+17.24%	
	BA, MPR 50%	+48.02%		+24.72%	
	BA, MPR 75%	+60.94%		-18.26%	
		With BA versus without BA			
		AVs		HDVs	
Effect of considering behavioral adaptation (BA)	More Defensive AVs MPR 25%	-19.11%		+16.44%	
	More Defensive AVs MPR 50%	-14.72%		+32.14%	
	More Defensive AVs MPR 75%	0%		+0.56%	
	NR *Less Defensive* AVs MPR 25%	+0.35%		+0.37%	
	NR *Less Defensive* AVs MPR 50%	0%		+2.16%	
	NR *Less Defensive* AVs MPR 75%	+0.52%		+2.94%	
	R *Less Defensive* AVs MPR 25%	-27.78%		+7.41%	
	R *Less Defensive* AVs MPR 50%	-24.33%		+28.06%	
	R *Less Defensive* AVs MPR 75%	-11.57%		+61.03%	

*BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; MPR – Market Penetration rate; R – recognizable; NR – not-recognizable

A striking observation is how the AVs' recognizability affects differently the delays for AVs and HDVs on the major road. When *Less defensive* AVs are recognizable, they experience lesser delays compared to when they are not-recognizable. On the other hands, HDVs on the major road experience larger delays when the *Less defensive* AVs are recognizable compared to when not-recognizable.

It is also interesting to observe that the difference in delay between *More defensive* AVs and not-recognizable *Less defensive* AVs is small at lower penetration rates (e.g., ~1% at MPR 25%). However, the delay difference between *More defensive* AVs and recognizable Less *defensive* AVs is much larger even at lower penetration rates (~40% at MPR 25%).

It can also be observed that not considering behavioral adaptation results across all conditions in an underestimation of the delay for HDVs on the major road. However, for AVs on the major road, not considering behavioral adaptation generally results in an overestimation of their experienced delay.

6.3 Queue length on minor road

At the end of each simulation run, there were vehicles remaining in the queue on the minor road. The number of vehicles remaining in queue is an indicator of the queue length on the minor road. Figure 12 shows the number of vehicles remaining in queue on the minor road in different conditions. The longest queue was found to be in conditions with *More defensive* AVs with a 75% penetration rate. The shortest queue was found in the conventional traffic condition. Table 12 presents the percentages differences in queue lengths between the different conditions organized by the research questions.

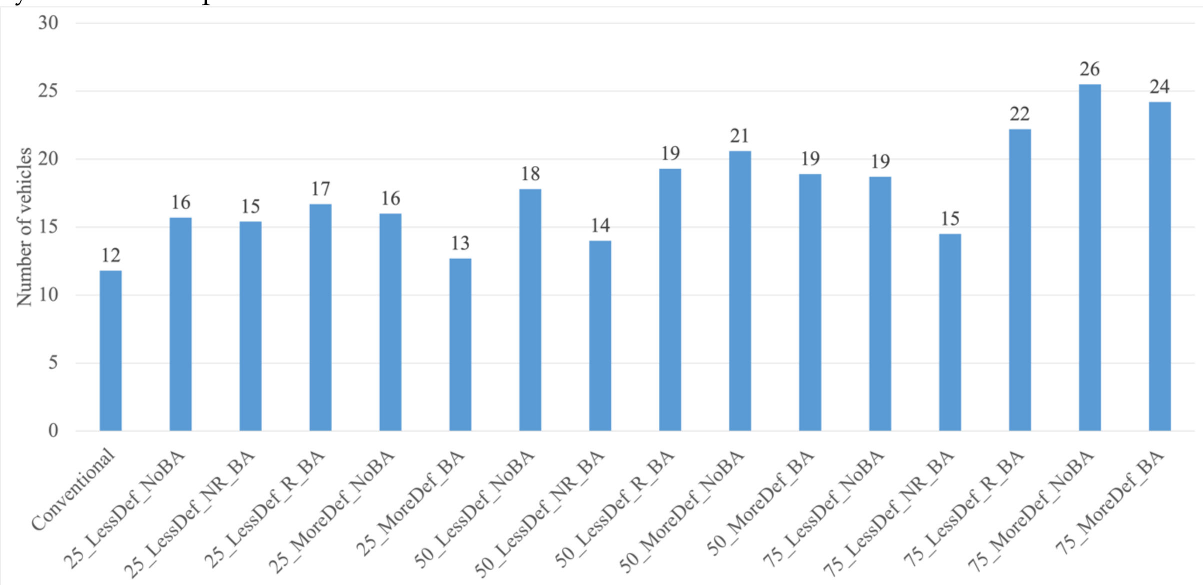

Figure 12. Number of vehicles remaining in queue on the minor road in different conditions at the end of each simulation run (R – Recognizable; NR – Not Recognizable; BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

In general, an increase in MPR results in an increase in queue length on the minor road, except when behavioral adaptation is considered in non-recognizable *Less defensive* AV traffic. Also, the queue length is greater when *Less defensive* AVs are recognizable compared to when not. The queue length on the minor road is smaller when behavioral adaptation is considered compared to when it is not considered, except when *Less defensive* AVs are recognizable.

Table 12. Percentage change in queue length on the minor road between different conditions

	Condition	Change in queue length (percentage)	
		MPR from 25% to 50%	MPR from 50% to 75%
Effect of Market Penetration Rate	No BA, More defensive AVs	+31.25%	+23.81%
	No BA, Less defensive AVs	+12.50%	+5.56%
	BA, More defensive AVs	+46.15%	+26.32%
	BA, NR Less defensive AVs	-7%	+7.14%
	BA, R Less defensive AVs	11.76%	+15.79%
	R versus NR *Less defensive* AVs		
Effect of recognizability	BA, MPR 25%		+13.33%
	BA, MPR 50%		+35.71%
	BA, MPR 75%		+46.67%
	More defensive versus Less defensive AVs		
Effect of AV driving style	No BA, MPR 25%		0.00%
	No BA, MPR 50%		+16.67%
	No BA, MPR 75%		+36.84%
	More defensive AVs versus NR *Less defensive* AVs		
	BA, MPR 25%		-13.33%
	BA, MPR 50%		+35.71%
	BA, MPR 75%		+60.00%
	More defensive AVs versus R *Less defensive* AVs		
	BA, MPR 25%		-23.53%
	BA, MPR 50%		0.00%
	BA, MPR 75%		+9.09%
	With BA versus without BA		
Effect of considering behavioral adaptation (BA)	More defensive AVs MPR 25%		-18.75%
	More defensive AVs MPR 50%		-9.52%
	More defensive AVs MPR 75%		-7.69%
	NR *Less defensive* AVs MPR		-6.25%
	NR *Less defensive* AVs MPR		-22.22%
	NR *Less defensive* AVs MPR		-21.05%
	R *Less defensive* AVs MPR 25%		+6.25%
	R *Less defensive* AVs MPR 50%		+5.56%
	R *Less defensive* AVs MPR 75%		+15.79%

BA – Behavioral adaptation; MPR – Penetration rate; R – recognizable; NR – non-recognizable

7 Discussion & Conclusion

The discussion of the results is organized according to the research questions. For each research question, the results for the minor road are discussed first followed by the results for the major road. For the first three research questions, we discuss the results when behavioral adaptation is considered. In the fourth research question, we discuss the effect of considering or not considering behavioral adaptation on the performance indicators.

7.1 *What is the effect of* ***AVs' penetration rate*** *on the efficiency of mixed traffic at priority T-intersection?*

For vehicles on the **minor road**, the delay increases with an increase of AV penetration rate on the major road. This occurs both when AVs are *More defensive* and when they are *Less defensive*

(recognizable and non-recognizable). This could be because both *Less defensive* and *More defensive* AVs as defined in this study have larger desired headways than most HDVs. Therefore, vehicles on the major road are more spread (but still not with an enough big gap to merge from the minor road) and have smaller gaps between groups (platoons) of vehicles arriving at the intersection. Therefore, more vehicles on the minor road end up waiting at the stop line before an acceptable gap is available. The increase in delay is especially high when AVs are *More defensive*, with more than a +100% increase in median delay per minor vehicle when the *More defensive* AV penetration rate increases from 50% to 75%. In absolute terms, this increase in median delay is approximately +100 seconds per minor road vehicle. As *More defensive* AVs have larger time headways than *Less defensive* AVs, the increase in delay for minor road vehicles with increasing penetration rate is larger for scenarios with *More defensive* AVs than scenarios with *Less defensive* AVs. **Therefore, there is a clear trend that delay for minor road vehicles increases with an increase in AV penetration rate on the major road.**
The effects of AV penetration rate on the delay of AVs on the **major road** is much less noticeable. The largest increase in median delay per AV due to an increase in the penetration rate was +22.62% when the penetration rate of *More defensive* AVs increased from 50% to 75%. In absolute terms, this increase in median delay was only 0.76 seconds per AV on the major road. The effects of AV penetration rate on the delay of HDVs on the major road is mixed. The largest increase in HDVs' median delay of +30.59% was in *More defensive* AV traffic, when the AV penetration rate increased from 25% to 50%. In absolute terms, this increase was only 0.52 seconds per HDV on the major road. **Therefore, increasing AV penetration rate does not seem to affect the delay of vehicles (both AVs and HDVs) on the major road in a meaningful way.**

7.2 *What is the effect of* ***AVs' recognizability*** *on the efficiency of mixed traffic at priority T-intersection?*

Recognizability significantly affected the gap acceptance behavior only in *Less defensive* AV traffic. For vehicles on the **minor road**, the median delay was larger when *Less defensive* AVs were recognizable compared to when being non-recognizable. This held true at all penetration rates. At a penetration rate of 75% *Less defensive* AVs, the median delay per minor road vehicle was +81.67% (74.9 seconds) larger when AVs were recognizable compared to when non-recognizable. This is because minor road vehicles are less likely to accept a gap in front of a recognizable *Less defensive* AV, in-line with what was reported in Reddy et al. (2022). **Thus, *Less defensive* AVs result in increased delay for minor road vehicles when AVs are recognizable compared to non-recognizable.**
For *Less defensive* AVs on the **major road**, the median delay was smaller when they were recognizable compared to when they were not recognizable. This is because *Less defensive* AVs are less likely to be cut-off by minor road vehicles when they are recognizable compared to when they are non-recognizable. However, the difference in the median delays between recognizable and non-recognizable *Less defensive* AVs appeared to reduce with higher penetration rates. At a penetration rate of 25% *Less defensive* AVs, the median delay per AV vehicle was -28.03% (0.8 seconds) smaller when AVs were recognizable compared to when they were not recognizable. And at a penetration rate of 75% *Less defensive* AVs, the median delay per AV vehicle was -12.03% smaller when AVs were recognizable compared to when they were not recognizable. Interestingly, for HDVs on the major road, the median delay was larger when *Less defensive* AVs were recognizable compared to non-recognizable. This is probably because HDVs in such a scenario would be more likely to accept a gap in front of an HDV than in front of a recognizable *Less defensive* AV. This difference in median delay increased with an increase in the penetration rate of *Less defensive* AVs. At a penetration rate of 75% *Less defensive* AVs, the median delay per major road HDV was +56.43% (0.8 seconds) larger when AVs were recognizable compared to when they were not recognizable. **Although recognizability of *Less defensive* AVs seems to have an effect on the delay of major road vehicles, the magnitude of this effect appears to be very small.**

7.3 *What is the effect of **AVs' driving style** on the efficiency of mixed traffic at priority T-intersection?*

At higher penetration rates, **minor road** vehicles were found to experience larger delays when AVs were *More defensive* than when AVs were *Less defensive* and non-recognizable. The largest difference was at an AV penetration rate of 75% where the median delay per minor road vehicle was +128.3% (117.6 seconds) larger when AVs were *More defensive* compared to when AVs were *Less defensive* and non-recognizable. This trend was also observed with recognizable *Less defensive* AVs. The difference between the median delay per minor road vehicle when AVs were *More defensive* and when they were *Less defensive* and recognizable increased with increasing AV penetration rate (note that recognizability does not play a role in *More defensive* AVs). At a penetration rate of 25%, the median delay per minor road vehicle was -38.28% (35.7 seconds) smaller when AVs were *More defensive* compared to when AVs were *Less defensive* and recognizable. On the other hand, at a penetration rate of 75%, the median delay per minor road vehicle was +25.68% (42.8 seconds) larger when AVs were *More defensive* compared to when AVs were *Less defensive* and recognizable. **Therefore, at a larger penetration rate, the delay for minor road vehicles is larger when AVs are more defensive as compared to when AVs are recognizable and less defensive**. In (Reddy et al., 2022), drivers' critical gaps were the smallest for *More defensive* recognizable AVs and largest for *Less defensive* recognizable AVs. The difference with the current study is the traffic distribution of the approach road. While in the driving simulator, traffic was uniformly distributed, in the simulation, approaching road traffic followed a Poisson distribution as would be in real life. Hence, the delay effects are less straightforward to predict.

For AVs on the **major road**, the median delay was larger for *More defensive* AVs compared to *Less defensive* AVs, especially at higher penetration rates. At a 75% penetration rate, the median delay per *More defensive* AV was +41.58% (1.2 seconds) larger than that for non-recognizable *Less defensive* AVs, and +60.94% (1.6 seconds) larger than that for recognizable *Less defensive* AVs. For HDVs on the major road, the median delay was generally larger in *More defensive* AVs traffic than in *Less defensive* AV traffic. The largest difference was at an AV penetration rate of 50%, where the median delay per major road HDV in *More defensive* AV traffic was +56.34% (0.8 seconds) larger than in non-recognizable *Less defensive* AV traffic. **When the absolute change in delay is considered, it does not appear that there is a very meaningful difference in delay with AV driving style, for vehicles (both AVs and HDVs) on the major road.**

7.4 *What is the effect of **considering human drivers' behavioral adaptation** in mixed traffic in the context of the above questions?*

The effect of considering behavioral adaptation on the measured median delay for **minor road** vehicles is primarily noticeable when AVs are *Less defensive* and recognizable. Considering behavioral adaptation results in an increase in median delay for minor road vehicles in recognizable *Less defensive* AV traffic, when compared to not considering behavioral adaptation. The increase in median delay per vehicle is +63.28% (36.1 seconds) at 25% penetration rate, +49.24% (33.8 seconds) at 50% penetration rate, and +75.54% (71.7 seconds) at 75% penetration rate. In other scenarios, the difference in median delay for minor road vehicles before and after considering behavioral adaptation is not considerable. Compared to conventional traffic scenario (100% HDV traffic), the median delay per minor road vehicle in recognizable *Less defensive* AV traffic considering behavioral adaptation is +138.9% (54.2 seconds) larger at 25% penetration rate, +162.9% (63.5 seconds) larger at 50% penetration rate, and +327.3% (127.6 seconds) larger at 75% penetration rate. If behavioral adaptation was not considered, the median delay per minor road vehicle in conventional traffic compared to *Less defensive* AV traffic would be +46.4% (18 seconds) larger at 25% penetration rate, +76.2% (29.7 seconds) larger at 50% penetration rate, and +143.4% (55.9 seconds) larger at 75% penetration rate. Therefore, recognizable *Less defensive* AVs will result in a relatively large increase in delay for minor road vehicles compared to conventional traffic, when behavioral adaptation is considered. **Considering behavioral adaptation results in a significant change in the measured delay for minor road traffic.**

For AVs on the **major road**, the effect of considering behavioral adaptation is relatively smaller. The general trend is that considering behavioral adaptation reduces the measured delay for AVs on the major road. The difference in median delay is relatively more noticeable for recognizable *Less defensive* AVs, with the largest decrease in median delay per AV after considering behavioral adaptation compared to not considering behavioral adaptation being -27.8% (0.8 seconds in absolute terms). The decrease of 0.8 seconds does not seem very significant. For HDVs on the major road, the effect of considering behavioral adaptation is also relatively smaller. The most noticeable difference is in recognizable *Less defensive* AV traffic, where considering behavioral adaptation compared to not considering behavioral adaptation results in an increase in delay per HDV on the major road by 61% (0.83 seconds in absolute terms). Again, 0.83 seconds does not seem very significant. **Therefore, considering behavioral adaptation does not seem to have a meaningful impact on the measured delay for AVs and HDVs on the major road, compared to not considering behavioral adaptation.**

8 Threats to validity of results

This research made certain assumptions and has some limitations. Below, we discuss the threats to the validity of the results:

Short waiting time before gap acceptance: In the driving simulator experiment, drivers did not need to wait for a long time before accepting a gap. This made it impossible to get insights into the effect of minor road vehicle waiting time on their gap-acceptance behavior. It may be expected that longer waiting times make drivers more impatient and accept smaller gaps (Zohdy et al., 2010), further encouraged by the "back pressure" from vehicles waiting behind in the queue. Minor road drivers accepting smaller gaps would cause larger delays to major road vehicles, and/or cause delays to a larger number of major road vehicles. Minor road vehicles could experience smaller delays as they accept smaller gaps. However, the disruption caused to the major road could reduce the available gaps on the major road further upstream causing smaller offered gaps, until the disruption is alleviated. This may consequently result in minor road vehicles waiting longer to get an offered gap.

Effect of the appearance of the AVs: AVs appearance (the color and the model) in the simulator could have had an effect on the gap acceptance behavior. It could be that "ordinary" colors of the AV such as white or grey could lead drivers to perceive the AV as more defensive, as compared to a bright color such as yellow. Also, the build/model of the car could affect how they are perceived. A car with clearly visible LiDAR and camera sensors may suggest that the car can detect other vehicles well, thus increasing the trust in the AV.

We only considered human drivers gap acceptance: In this research, we only considered AVs to be present on the major road due to no insights on gap acceptance behavior of AVs on the minor road. In reality AVs would be mixed in traffic. This is also the reason why we modelled only one intersection as opposed to a network of intersections as otherwise we would need to define AVs gap acceptance behavior (because AVs on the major road would approach the following intersection as minor road traffic). It is possible that AVs have a more conservative gap acceptance behavior compared to HDVs resulting in acceptance of large gaps, which may be better for the major road vehicles, but can increase the delay and queue length for the minor road.

Limitations of using a driving simulator: The empirical data was collected from a driving simulator experiment. The experience in a driving simulator is different from driving in real life due to aspects such as the physical experience of risk and speed, the knowledge that one is being observed, and sense of urgency in real life to arrive at work or home. It could be that in real life driving, drivers drive safer (due to greater perception of risk), accepting larger gaps; or even riskier (due to not being observed, and/or because of greater time pressure), accepting smaller gaps.

Long term behavioral adaptation: Gap acceptance in this study was modelled based on the behavior of participants in a simulator on a specific day. In reality, there may be a long-term behavioral adaptation that could be different from the short-term behavioral adaptation. For instance, drivers may get used to recognizing AVs and understanding and anticipating their behavior. This could cause them to drive even more aggressively if they anticipate AVs to be defensive, thereby accepting smaller gaps in front of AVs (and possibly also in front of HDVs due to behavioral adaptation); or to drive more defensively if they anticipate AVs to be aggressive; thereby accepting larger gaps.
Driving style of AVs: The *More defensive* and *Less defensive* AVs in the driving simulator differed from the HDVs in their desired time headway and desired speed. It is probable that there will be more behavioral differences such as with acceleration and deceleration (Wang et al., 2023). This was not considered in this study. Considering these additional differences between the two AV driving styles are expected to result in an even more distinct interactions of HDVs with them.
Effect of penetration rate: We assumed that the gap acceptance behavior (the model) of human drivers remains constant irrespective of the AV penetration rate. It is possible that greater penetration rates of AVs result in a different effect on gap acceptance behavior of human drivers.

9 Recommendations for policy and future research

AVs are expected to become increasingly present on our roads. Human drivers, who will share the road and interact with these AVs, might interact differently than when interacting with other HDVs. This could have implications for traffic efficiency and therefore on policy decisions relevant to the deployment of AVs. In this study, we investigated the potential impact on the traffic efficiency at priority T-intersections. Human-driven vehicles on the minor road waited at a stop line to accept a suitable gap between vehicles on the major road composed of both AVs and HDVs. We found that the delay for vehicles on the major and minor roads is impacted by aspects such as AVs penetration rate, AVs recognizability and driving style, and whether behavioral adaptation was considered in gap acceptance.
Higher penetration rates lead to larger delays for minor road vehicles. Considering behavioral adaptation of minor road vehicles when AVs on the major road were recognizable and less defensive led to a change in the measured delay per vehicle compared to when behavioral adaptation was not considered. It is interesting to note that the lowest delay for minor road vehicles and for major road vehicles was in conventional traffic condition. Moreover, the number of vehicles remaining in the queue on the minor road was also the lowest in the conventional traffic condition. This suggests that as far as traffic efficiency is concerned at priority T-intersections, conventional traffic is the most efficient compared to any condition with the AVs considered in this study. This raises the question of the benefit of AVs for traffic efficiency. Policymakers must therefore gain an accurate understanding of the precise benefits brought by AVs. Another important insight is the difference between the delays for less defensive AVs and HDVs on the major road, with respect to the recognizability of AVs. When less defensive AVs are recognizable, their delays decrease, but the delays for the other HDVs on the major road increases. This raises an important question of equity, that must be considered by policymakers.
There could be some practical measures that can improve traffic efficiency in mixed traffic. To reduce the delays at priority intersection, AVs may need to adjust their gaps while approaching the intersection. This would result in larger gaps between arriving platoons of major road vehicles, resulting in more opportunities for gap acceptance for minor road vehicles. The build-up of queue on the minor road could be an issue when there is limited road length available on the minor road due to, for example, another intersection upstream. Infrastructure to Vehicle (I2V) and Vehicle to Vehicle (V2V) communication could be designed to trigger changes in the headways of AVs when the minor road queue length exceeds by a critical margin. Road authorities and policymakers can take these aspects into consideration when making infrastructure-level decisions.

The magnitude of the delay differences is important to note. The delays for minor road vehicles for the different conditions were much larger than the delays for major road vehicles, as was expected. Policymakers and road authorities should consider whether the delays and the differences in delays between different scenarios are meaningful (or important enough). The delay per vehicle in seconds could be converted to total delay in hours per year. For example, assuming a minor road peak hour traffic volume of 200 vehicles per hour, and 4 hours of peak hour traffic every day, the total delay for minor road vehicles for over a year can be calculated for different conditions. For the condition of 75% *Less defensive* AVs without considering behavioral adaptation, the total annual delay for all vehicles would be about 7700 hours (i.e., 38.5 hours per vehicle per year), and for the condition of 75% *Less defensive* recognizable AVs with behavioral adaptation it would be about 13500 hours for all vehicles (i.e., 67.5 hours per vehicle per year). The difference is 5800 hours per year, which is the unaccounted delay if behavioral adaptation was not considered in recognizable *Less defensive* AV traffic. Similarly, the total annual delay for minor road vehicles in conventional traffic condition is about 3200 hours, whereas for the condition 75% more defensive AVs with behavioral adaptation it is about 17000 hours, resulting in a difference of about 13800 hours. It must be considered whether this is meaningful enough to adopt any countermeasures. This is for policymakers to decide.

Future research on traffic efficiency effects of mixed traffic must consider behavioral adaptation when modelling gap acceptance behavior in mixed traffic as it was found that considering behavioral adaptation results in a large change in the measured delays for minor road vehicles when AVs were recognizable and less defensive in mixed traffic. Field tests must be conducted to study human drivers gap acceptance behavior in real life as compared to a simulator environment. The effect of longer waiting times at the intersection in mixed traffic is also important to study, in combination with "back pressure" from vehicles waiting behind the subject vehicle. Future studies must design the appearance and driving styles of AVs to be more realistic and based on the current or realistic expected future driving styles of AVs. The effect of penetration rate on the gap acceptance behavior is an important topic to investigate. Also, future research in this direction should look at gap acceptance with AVs also on the minor road by defining gap acceptance behavior of AVs. It is also noteworthy to standardize the data collection methodology and analysis method for such gap acceptance behavior prediction studies, using benchmarking approaches such as the one described in Schumann et al. (2023). This would allow for a more systematic and complete evaluation of the models. Additionally, traffic safety indicators must be included in the analysis to gain traffic safety insights, and to further understand the balance between traffic efficiency and safety. Finally, long term behavioral adaptation would be important to study to understand whether and how human drivers change their behavior as they get more experienced with interacting with AVs and the implications on traffic efficiency and safety.

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Acknowledgements

This work was supported by Applied and Technical Sciences (TTW), a subdomain of the Dutch Institute for Scientific Research (NWO) through the Project Safe and Efficient Operation of Automated and Human-Driven Vehicles in Mixed Traffic (SAMEN) under Contract 17187. The authors also acknowledge the contribution of Dr. Wouter Schakel who implemented the scenarios in the driving simulator software.

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Appendix A

In the microsimulation environment, an unsignalized T intersection was initially generated by deactivating the priorities. Based on the framed simulation scenarios, traffic volumes were input in accordance with the distinct vehicle categories present, including Autonomous Vehicles (AVs) and Heavy Duty Vehicles (HDVs) on the main road, while HDVs exclusively on the minor road. Following this, iterative simulation runs were conducted for each scenario, employing a diverse set of ten seeds to ensure robust results. During the simulation process, the Traffic Control Interface (TRACI) script was invoked as vehicles originating from the minor road traverse into the intersection zone. It was at this juncture that the behavior of these vehicles, particularly their inclination to accept or reject available gaps in traffic flow, was steered by the gap acceptance model. This model served as a guiding principle, influencing how vehicles navigate through the intersection based on their assessment of viable gaps in the oncoming traffic.
Further, to understand the traffic characteristics, the detailed trajectory information, comprehensive records of individual vehicle trips were recorded. These recorded data served as the foundation for evaluating the performance and behavior of the simulated traffic scenarios. Further, the processes are detailed in Figure 13.

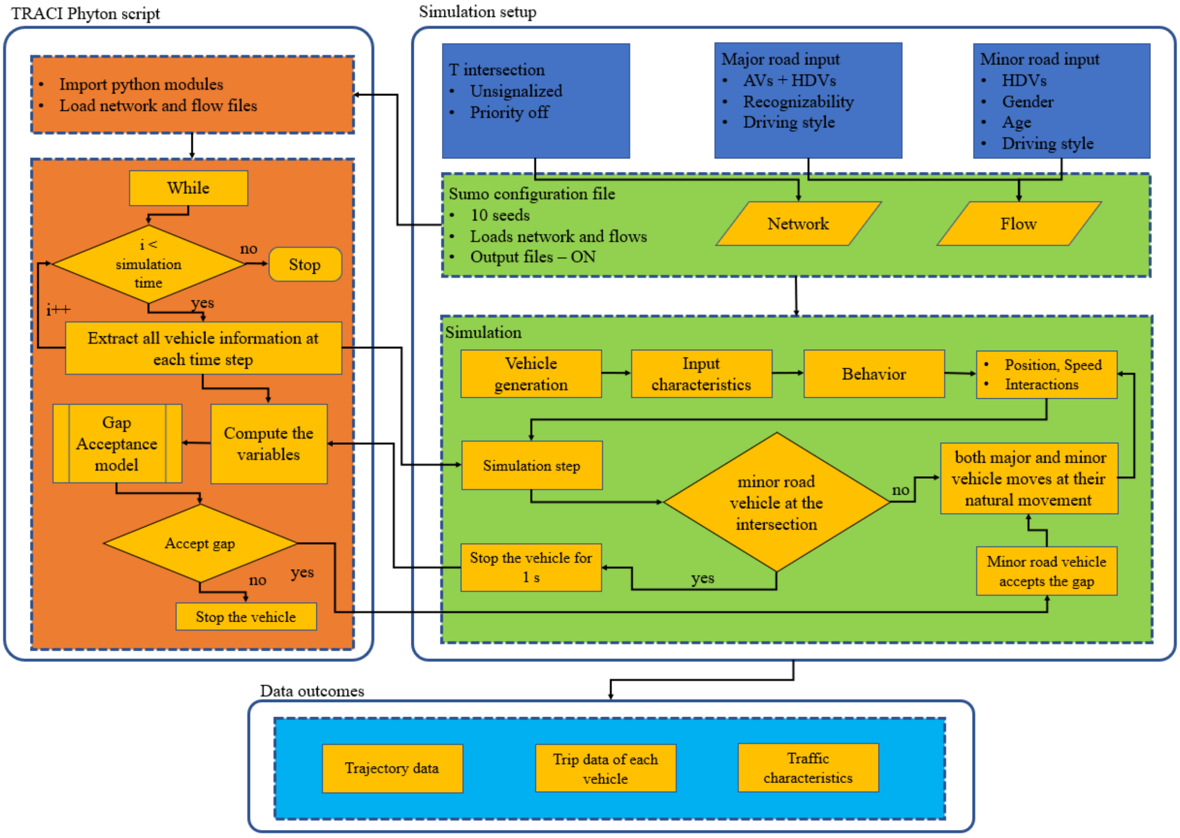

Figure 13. Microscopic traffic simulation setup for modelling the gap acceptance behavior.