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Delft University of Technology

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Human Driving Behavior when Interacting with Automated Vehicles and the Implications on Traffic Efficiency

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by

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Dedicated to those who did not have the same opportunities as me

Preface

Writing this thesis has been a rewarding and a challenging journey, and I'm deeply grateful to those who supported me along the way. Without their guidance, encouragement, and patience, this work wouldn't have been possible.

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As I write these acknowledgements, I recall the numerous times I have heard over the past years of the importance of being an independent researcher. After now acknowledging over 100 people - and I am sure I have missed several others - whose support and contribution I needed to complete this PhD journey, I believe to have proved to myself that I am in fact extremely dependent on my community; and this has convinced me that our goal should in fact be to build a community that provides the right conditions and support to help all the individuals to realize and achieve their potential.

My deepest gratitude to all these people who touched and shaped this part of my life,

Nagarjun

Delft, April 2025

Summary

Introduction

As (partially) automated vehicles (AVs) become increasingly prevalent on public roads, attention is also increasing on their integration in mixed traffic (traffic composed of AVs and human-driven vehicles), and on the impacts they could have on traffic flow, traffic safety, and road infrastructure. One aspect that has received relatively little attention so far is the effect of AVs on the driving behavior of human-driven vehicles (HDVs) in mixed traffic. The interactions of AVs with HDVs can be different than the interactions of HDVs with other HDVs. Recently, growing evidence has emerged in scientific literature supporting this. Such changes include HDVs driving closer while following behind AVs or making more frequent lane changes while driving in mixed traffic. These changes can have negative or positive effects on the overall traffic safety and efficiency. Currently, there is a limited understanding of which mixed traffic factors affect HDVs' driving behavior and the nature of their effects. Therefore, this dissertation focused on studying the impacts of AVs on the behavior of HDVs to gain a better and deeper understanding of any potential changes in HDV driving behavior, referred to in this dissertation as behavioral adaptations. The main research question of this dissertation is:

What are the impacts of automated vehicles on the driving behavior of human-driven vehicles, and their consequences on mixed traffic efficiency?

Figure S 1 is a depiction of the scope of this dissertation, highlighted by the orange shade. It positions the HDV in the center, being affected by three different sets of factors: the road environment (e.g., weather, infrastructure), the traffic (other road users), and the driver (personal characteristics). These factors influence the driving behavior of the HDVs, such as car-following and gap acceptance, which ultimately impact the overall traffic aspects such as safety andefficiency. In this dissertation, I focused on car-following, overtaking, and gap acceptance behavior, and the impact of gap acceptance on traffic efficiency. These were partly selected based on how driving behavior is generally characterized and studied in traffic engineering, covering both longitudinal (car-following) and lateral behaviors

(overtaking and gap acceptance); and partly on the insights derived during this research. Gap acceptance behavior was chosen to study the impact on traffic efficiency because of the impact it can have on the traffic flow on the road to which traffic is merging on to and on the road network upstream of the intersection. Moreover, during gap acceptance, drivers have the opportunity to observe the oncoming vehicles, possibly being more prone to mixed traffic factors such as AV appearance. To answer the main research question, the following sub research questions (RQs) were defined, which are also depicted as thick arrows in Figure S 1:

1. What are the potential behavioral adaptations of human drivers during their interactions with AVs?
2. What is the impact of AVs on the car following behavior of HDVs?
3. How do human drivers perform gap acceptance maneuvers in mixed (automated and human-driven) traffic at priority T-intersections?
4. How does mixed traffic affect the traffic efficiency of priority T-intersections?

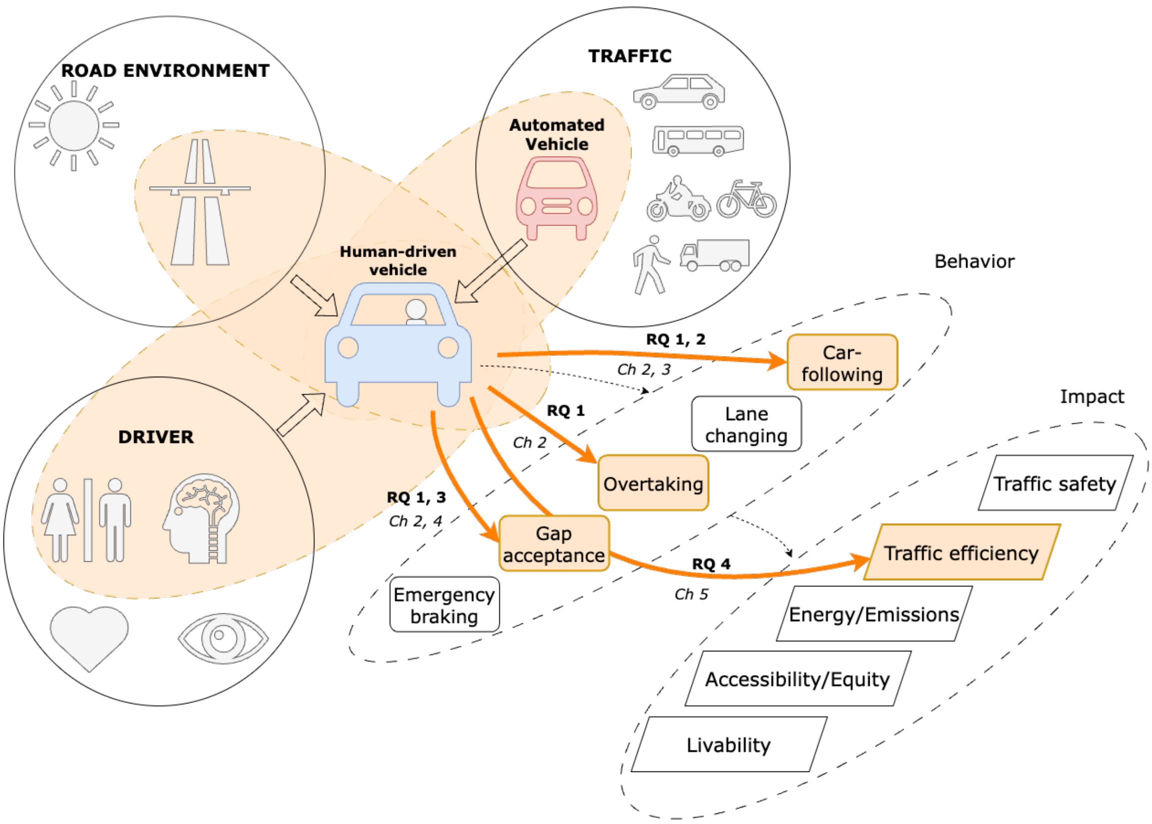


Figure S 1: Conceptual framework as an outline for this dissertation.

Methods

To answer the research questions, this dissertation adopted empirical data collection methods such as driving simulators and field tests. As AVs currently do not widely operate on public roads, and because there is very limited available data on interactions between AVs and HDVs, data collection efforts were made for this dissertation. Driving simulators help to study empirically the behavior of drivers in a safe and controlled virtual environment, where different traffic conditions can be tested in a cost-effective manner. Field tests allow the investigation of driving behavior in a real-life setting therefore having potentially greater validity than driving simulator studies, however having less possibilities to control the environmental conditions compared to driving simulators. Therefore, this dissertation used a combination of these two methods.

This dissertation also entailed mathematical modelling of driving behaviors of interest. For instance, mathematical models of car following behavior and gap acceptance behavior were estimated using empirical data collected from the driving simulator experiments. These models were also implemented in microsimulation to define HDVs' behaviors. With the help of microsimulation, macroscopic indicators of traffic efficiency in mixed traffic was studied.

Results

The main findings are summarized inTable S 1 and Table S 2. The tables show how different behaviors of human drivers are affected by specific mixed traffic factors. The driving behaviors are represented by certain indicators, and the specific nature of the effect. They also show which study and chapter of this dissertation the finding relates to. This dissertation investigated the effects of several factors on different indicators. The tables only present the effects that resulted in a (significant) change in the indicators, only for mixed traffic specific factors. The factors did not have any significant effect on the other indicators. The complete list of factors considered in this dissertation were: Mixed traffic specific factors (AV appearance, AV driving style, trust in AVs, AV penetration rate, considering behavioral adaptation), general factors (Driver age, driver gender, driver driving style). The complete list of indicators investigated were: Car-following (Jam spacing, Desired velocity, Safe time headway, Maximum acceleration, Comfortable deceleration), Gap acceptance (Accepted gap size, Critical gap, probability of accepting a gap), Overtaking (Headway after overtaking, Lateral distance while overtaking), Traffic efficiency at priority T intersection(Delay per vehicle on minor road, Delay per vehicle on major road, Queue length).

Factors related to mixed traffic were observed to have several effects on HDV behavior and on behavioral adaptation. Specifically, I focused on the following mixed traffic factors: AV appearance, AV driving style, Trust in AVs, and AV penetration rate. I investigated their effects on fundamental driving maneuvers of HDVs including HDVs' car-following behavior, gap acceptance behavior, and overtaking behavior. I then investigated the impact of the changes in gap-acceptance behavior on traffic efficiency at priority T-intersections. These behaviors were measured using different indicators as shown in Table S 1 and Table S 2, where the specific directions of the effects on these indicators are also presented.

In addition to the specific results of this dissertation, the following key takeaways also result from the combination and discussion of all the findings:

1. **Mixed traffic factors affect human drivers' behaviors, and this also has implications on traffic efficiency at a macroscopic level**. For example, in a driving simulator experiment, human drivers tended to accept larger gaps in the major road traffic stream when they had to merge in front of a recognizable AV that was driving less defensively. After implementing HDVs' gap acceptance behavior in microsimulation, it showed that the delay for minor road HDV vehicles was larger when the major road traffic had less defensive recognizable AVs.
2. **Not considering behavioral adaptation of HDVs while predicting the traffic efficiency of mixed traffic could lead to inaccurate results**. For example, the microsimulation study showed that not considering behavioral adaptations of HDVs in gap acceptance could lead to an underestimation of delay of minor road vehicles by about 75% (at 75% AV penetration rate).
3. **There is a stronger tendency for behavioral adaptations to occur in the forward field of view of AVs**. Interactions in the forward field of view of AVs could be

performing gap acceptance in front of an AV from standstill or merging in front of an AV after overtaking. For example, in the field test, drivers were willing to merge in front of AVs at closer distances than in front of HDVs. Also, they merged closer in front of AVs after overtaking them, as compared to HDVs. Behavioral adaptations can still occur in other behaviors and directions, only that the extent could be smaller than in the forward field of view. In a driving simulator experiment, we found behavioral adaptation also in car-following where drivers had smaller desired standstill (jam) distance when following an AV compared to an HDV.

4. **If drivers do not recognize a vehicle as an AV, then drivers tend to imitate the driving behavior of the vehicle**. For example, in a driving simulator experiment, we found that drivers accepted larger gaps during gap acceptance when the (not-recognizable) AVs drove more defensively and accepted smaller gaps when the (not-recognizable) AVs drove less defensively.
5. **If drivers recognize a vehicle as an AV, then the direction and extent of the behavioral adaptations depend on the level of trust drivers have in AVs.** For example, in a driving simulator experiment, we found that drivers accepted smaller gaps during gap acceptance when the (recognizable) AVs drove more defensively and accepted larger gaps when the (recognizable) AVs drove less defensively. In the field test, when positive information (trust-building) about AVs was provided to drivers, they merged even closer in front of AVs after overtaking.

Practical implications and future research directions

The results of this dissertation have implications for several stakeholders. **Drivers of manual vehicles** must become aware of the behavioral adaptations they could undergo. **AV users** must also be conscious of how other drivers could change their behavior when interacting with them. **Road authorities** must make an evaluation of how meaningful/significant the impacts of behavioral adaptation are, and what kind of traffic management and infrastructural measures they can take. **Driving license and vehicle licensing** authorities also need to make guidelines on AV aspects such as their appearance and driving style, and to train human drivers to better manage the effects of behavioral adaptation. **AV car manufacturers** must investigate the effects of their vehicles and systems (appearance and behavior-related) on other road traffic. Also, AV manufacturers must make the users aware of what impacts of the different in-car settings could be on surrounding traffic. For instance, AV users can be informed that keeping defensive settings (such as large time headway) in adaptive cruise control could result in other drivers making closer maneuvers in front of the AVs. Ideally, a close collaboration between all stakeholders would be beneficial in ensuringgood driving conditions in mixed traffic.

In addition to the practical implications, this dissertation points to future research directions. Behavioral adaptations in other situations (e.g., motorways, urban roads) and driving maneuvers (e.g., lane changing, emergency braking) need to be investigated. Impacts on long term behavioral adaptation is also important to be studied as behaviors observed in the short-term could be very different from the long-term ones. Another interesting direction of research is the impact that eHMIs (external Human Machine Interfaces) of AVs on the interactions with HDVs. It is also important to investigate the interactions and impacts in mixed traffic having different penetration rates of AVs. Another crucial aspect that must be studied is the effect on traffic safety. Finally, the consequence of considering behavioral adaptation on the measured macroscopic effects on traffic efficiency must further be investigated. This topic has not been studied yet, except in this dissertation.

Table S 1: Overview of the effects of mixed traffic factors on human driver car-following and overtaking behavior

Behavior	Factor	Indicator	Effect		Study	Chapter
CAR-FOLLOWING	AV appearance	Desired velocity	↓	Smaller desired velocity when following vehicle appearing as AV compared to HDV.	Modelling using empirical data	3
		Safe time headway	↓	Smaller safe time headway when appearance is AV compared to HDV.		
		Jam spacing distance	↓	Smaller jam spacing distance when following vehicle appearing as AV compared to HDV.		
			↓	When following vehicle appearing as AV, jam spacing further reduces when drivers have higher trust in AVs		
		Comfortable deceleration	↑	When following vehicle appearing as AV, larger comfortable deceleration when drivers have higher trust in AVs		
	AV driving style	Desired velocity	↓	When driving style is AV, desired velocity smaller for drivers having higher trust in AVs.		
	Trust in AVs	Desired velocity	↓	When driving style is AV, desired velocity smaller for drivers having higher trust in AVs.		
		Jam spacing distance	↓	When following vehicle appearing as AV, jam spacing further reduces when drivers have higher trust in AVs		
		Comfortable deceleration	↑	When following vehicle appearing as AV, larger comfortable deceleration when drivers have higher trust in AVs		
OVERTAKING	AV appearance	Headway after overtaking	↓	Smaller headway after overtaking a recognisable AV compared to HDV.	Controlled field test	2

Table S 2: Overview of the effects of mixed traffic factors on human driver gap acceptance behavior and traffic efficiency

Behavior	Factor	Indicator		Effect	Study	Chapter
GAP ACCEPTANCE	**AV appearance**	**Accepted gap size**	↑	Largest accepted gap when AVs were recognizable, with less defensive driving style, and merging in front of an AV.	Driving simulator	4
		Critical gap	↓	Smaller critical gap when appearance is AV compared to HDV.	Controlled field test	2
			↓	When AVs are non-recognizable, critical gaps significantly smaller when AVs were less defensive compared to more defensive.	Driving simulator	4
			↑	But when recognizable, critical gaps significantly larger when AVs were less defensive compared to more defensive (when merging in front of AV).		
	AV driving style	**Accepted gap size**	↑	Largest accepted gap when AVs were recognizable, with less defensive driving style, and merging in front of an AV.		
		Critical gap	↑	When AVs are recognizable, critical gaps significantly larger when AVs were less defensive compared to more defensive (when merging in front of AV).		
			↓	When AVs are non-recognizable, critical gaps significantly smaller when AVs were less defensive compared to more defensive.		
	Trust in AVs	**Critical gap**	↓	Provision of positive information on AVs (increasing trust) reduces critical gap further.	Controlled field test	2
TRAFFIC EFFICIENCY AT PRIORITY T-INTERSECTION	**AV appearance**	**Delay for minor road vehicles**	↑	When AVs were less defensive, larger delays for minor road vehicles when AVs were recognizable compared to being non-recognizable.	Microsimulation	5
	AV driving style	**Delay for minor road vehicles**	↑	Increase in delay with AV penetration rate is larger when the major road has More defensive AVs compared to when it has Less defensive AVs.		
			↑	At larger penetration rates, delay for minor road vehicles is larger when AVs are more defensive as compared to when AVs are recognizable and less defensive.		
		Queue length	↑	Longest queue was observed in 75% AV penetration rate traffic with more defensive AVs (behavioral adaptation not considered); and shortest queue length was observed in conventional (fully HDV) traffic.		
	AV penetration rate	**Delay for minor road vehicles**	↑	Increase in AV penetration rate increased delay for minor road vehicles.		
		Queue length	↑	Longest queue was observed in 75% AV penetration rate traffic with more defensive AVs (behavioral adaptation not considered); and shortest queue length was observed in conventional (fully HDV) traffic.		
	Considering Behavioral Adaptation	**Delay for minor road vehicles**	↑	In less defensive AV traffic, considering behavioral adaptation results in an increase in delay per minor road vehicle by up to 75% (at 75% penetration rate).		

Samenvatting (Language - Dutch)

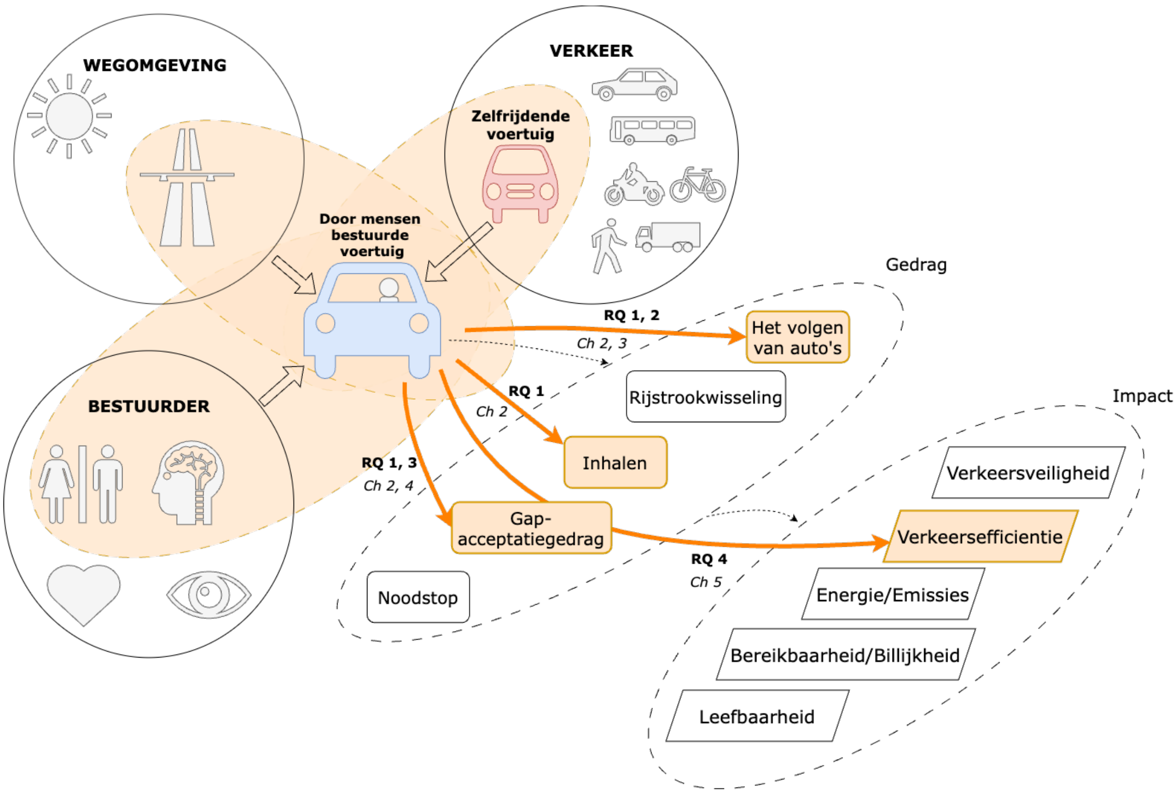
Introductie

Naarmate (gedeeltelijk) zelfrijdende voertuigen (ZV's) steeds vaker voorkomen op de openbare weg, neemt ook de aandacht toe voor hun integratie in gemengd verkeer (verkeer dat bestaat uit ZV's en door mensen bestuurde voertuigen), en voor de impact die ze kunnen hebben op de verkeersdoorstroming, verkeersveiligheid en weginfrastructuur. Een aspect dat tot nu toe relatief weinig aandacht heeft gekregen, is het effect van ZV's op het rijgedrag van door mensen bestuurde voertuigen (MBV's) in gemengd verkeer. De interacties van ZV's met MBV's kunnen verschillen van de interacties van MBV's met andere MBV's. Recentelijk is er steeds meer bewijs naar voren gekomen in de wetenschappelijke literatuur die dit ondersteunt. Dergelijke veranderingen omvatten MBV's die dichterbij rijden terwijl ze achter ZV's rijden of vaker van rijstrook veranderen tijdens het rijden in gemengd verkeer. Deze veranderingen kunnen negatieve of positieve effecten hebben op de algehele verkeersveiligheid en efficiëntie. Momenteel is er een beperkt begrip van welke gemengde verkeersfactoren van invloed zijn op het rijgedrag van MBV's en de aard van hun effecten. Daarom richt dit proefschrift zich op het bestuderen van de effecten van ZV's op het gedrag van MBV's om een beter en dieper inzicht te krijgen in mogelijke veranderingen in het rijgedrag van MBV's, in dit proefschrift aangeduid als gedragsaanpassingen. De centrale onderzoeksvraag van dit proefschrift is:

Wat zijn de effecten van geautomatiseerde voertuigen op het rijgedrag van door mensen bestuurde voertuigen en wat zijn de gevolgen ervan voor de efficiëntie van gemengd verkeer?

Figuur S 1 is een weergave van de afbakeningvan dit proefschrift, gemarkeerd door de oranje markering. Het positioneert de MBV in het midden en wordt beïnvloed door drie verschillende typenfactoren: de wegomgeving (bijv. weer, infrastructuur), het verkeer (andere weggebruikers) en de bestuurder (persoonlijke kenmerken). Deze factoren zijn van invloed op het rijgedrag van de MBV's, zoals het volgen van auto's en de "*gap-acceptatie*"(Beoordeling of er een voldoende veilige ruimte tussen twee voertuigen is om door te rijden of in te voegen), die uiteindelijk van invloed zijn op de algehele verkeersveiligheid en efficiëntie. Dit proefschrift richt zich op het volgen van auto's, inhalen en gap-acceptatiegedrag, en de impact van gap-acceptatie op verkeersefficiëntie. Deze fenomenen werden deels geselecteerd op basis van hoe rijgedrag over het algemeen wordt gekarakteriseerd en bestudeerd in de verkeerskunde, waarbij zowel longitudinaal (auto-volgend) als lateraal gedrag (inhalen en gap-acceptatie) wordt behandeld; En deels op de inzichten die tijdens dit onderzoek naar voren zijn gekomen. Er is gekozen voor gap-acceptatiegedrag om de impact op de verkeersefficiëntie te bestuderen vanwege de impact die het kan hebben op de verkeersstroom op de weg waarop het verkeer invoegt en op het wegennet stroomopwaarts van het kruispunt. Bovendien hebben bestuurders tijdens de gap-acceptatie de mogelijkheid om de tegenliggers waar te nemen, die mogelijk vatbaarder zijn voor gemengde verkeersfactoren zoals het uiterlijk van ZV's. Om de hoofdonderzoeksvraag te beantwoorden, zijn de volgende subonderzoeksvragen (RQ's) gedefinieerd, die in Figuur S 1 ook als dikke pijlen zijn weergegeven:

1. Wat zijn de mogelijke gedragsaanpassingen van menselijke bestuurders tijdens hun interacties met ZV's?
2. Wat is de impact van ZV's op het volggedrag van MBV's in de auto?
3. Hoe voeren menselijke bestuurders manoeuvres uit tijdens gap-acceptatie in gemengd (geautomatiseerd en door mensen aangestuurd) verkeer op prioritaire T-kruispunten?
4. Wat is de invloed van gemengd verkeer op de verkeersefficiëntie van prioritaire T-kruispunten?



Figuur S 1: Conceptueel kader als schets voor dit proefschrift

Methoden

Om de onderzoeksvragen te beantwoorden, is in dit proefschrift gebruik gemaakt van empirische gegevensverzamelingsmethoden zoals rijsimulatoren en veldtests. Omdat ZV's momenteel niet op grote schaal op de openbare weg worden gebruikt, en omdat er zeer beperkte gegevens beschikbaar zijn over interacties tussen ZV's en MBV's, zijn voor dit proefschrift gegevensverzamelingen uitgevoerd. Rijsimulatoren helpen om het gedrag van bestuurders empirisch te bestuderen in een veilige en gecontroleerde virtuele omgeving, waar verschillende verkeersomstandigheden op een kosteneffectieve manier kunnen worden getest. Veldtests maken het mogelijk om het rijgedrag in een real-life omgeving te onderzoeken, waardoor ze potentieel meer validiteit hebben dan rijsimulatorstudies, maar minder mogelijkheden hebben om de omgevingsomstandigheden te beheersen in vergelijking met rijsimulatoren. Daarom is in dit proefschrift een combinatie van deze twee methoden gebruikt.

Dit proefschrift omvat ook wiskundige modellering van relevant rijgedrag. Wiskundige modellen van het volggedrag van de auto en gap-acceptatiegedrag werden bijvoorbeeld geschat met behulp van empirische gegevens die waren verzameld uit de experimenten met de rijsimulator. Deze modellen waren ook in microsimulatie om het gedrag van MBV's te definiëren, om macroscopische indicatoren voor verkeersefficiëntie in gemengd verkeer te bestuderen.

Resultaten

De belangrijkste bevindingen zijn samengevat in Tabel S 1 en Tabel S 2. De tabel laat zien hoe verschillende gedragingen van menselijke bestuurders worden beïnvloed door specifieke gemengde verkeersfactoren. Het rijgedrag wordt weergegeven door bepaalde indicatoren en de specifieke aard van het effect. Ook is te zien op welke studie en hoofdstuk van dit proefschrift de bevinding betrekking heeft. Dit proefschrift onderzocht de effecten van verschillende factoren op verschillende indicatoren. De tabellen tonen alleen de effecten die resulteerden in een (significante) verandering van de indicatoren, specifiek voor factoren in gemengd verkeer. De factoren hadden geen significante invloed op de andere indicatoren. De complete lijst van factoren die in dit proefschrift werden beschouwd, was: factoren specifiek voor gemengd verkeer (uiterlijk van ZV's, rijstijl van ZV's, vertrouwen in ZV's, penetratiegraad van ZV's, gedragsaanpassing in overweging nemen), algemene factoren (leeftijd van de bestuurder, geslacht van de bestuurder, rijstijl van de bestuurder). De complete lijst van onderzochte indicatoren was: volgafstand (jam afstand, gewenste snelheid, veilige tijdsafstand, maximale acceleratie, comfortabele vertraging), gap-acceptatie (geaccepteerde gap-grootte, kritieke gap, kans op het accepteren van een gap), inhalen (afstand na het inhalen, laterale afstand tijdens het inhalen), verkeers efficiëntie bij prioritaire T-kruispunten (vertraging per voertuig op de kleine-weg(zijweg), vertraging per voertuig op de hoofdweg, wachtrijlengte).

Er werd waargenomen dat factoren die verband houden met gemengd verkeer verschillende effecten hebben op MBV-gedrag en op gedragsaanpassing. Specifiek richt het proefschrift zichop de volgende gemengde verkeersfactoren: ZV-uiterlijk, ZV-rijstijl, vertrouwen in ZV's en ZV-penetratiegraad. Het onderzoekt hun effecten op fundamentele rijmanoeuvres van MBV's, waaronder het autovolggedrag van MBV's, het acceptatiegedrag van gaten en inhaalgedrag. Vervolgens analyseert hetwat de impact is van de veranderingen in gap-acceptatiegedrag op de verkeersefficiëntie op prioritaire T-kruispunten. Dit gedrag werd gemeten aan de hand van verschillende indicatoren, zoals te zien is in Tabel S 1 en Tabel S 2, waar ook de specifieke richtingen van de effecten op deze indicatoren worden gepresenteerd.

Naast de specifieke resultaten van dit proefschrift, kunnen de volgende belangrijke conclusies worden getrokken uit de combinatie en analyse van alle bevindingen.:

1. **Gemengde verkeersfactoren beïnvloeden het gedrag van menselijke bestuurders, en dit heeft ook implicaties voor de verkeersefficiëntie op macroscopisch niveau**. In een experiment met een rijsimulator hadden menselijke bestuurders bijvoorbeeld de neiging om grotere gaten in de belangrijkste verkeersstroom te accepteren wanneer ze moesten invoegen voor een herkenbare ZV die minder defensief reed. Na het implementeren van het gap-acceptatiegedrag van MBV's in microsimulatie, bleek dat de vertraging voor kleine MBV-voertuigen groter was wanneer het grote wegverkeer minder defensief herkenbare ZV's had.

Tabel S 1: Overzicht van de effecten van gemengde verkeersfactoren op het volgen van auto's en inhaalgedrag van menselijke bestuurders.

<table>
<tr><th>Gedrag</th><th>Factor</th><th>Indicator</th><th colspan="2">Effect</th><th>Studie</th><th>Hoofdstuk</th></tr>
<tr><td rowspan="9">HET VOLGEN VAN AUTO'S</td><td rowspan="5">ZV-uitstraling</td><td>Gewenste snelheid</td><td>↓</td><td>Kleinere gewenste snelheid bij het volgen van een voertuig dat als ZV verschijnt in vergelijking met MBV.</td><td rowspan="9">Modelleren met behulp van empirische data</td><td rowspan="9">3</td></tr>
<tr><td>Veilige tijdvooruitgang</td><td>↓</td><td>Kleinere veilige tijdvooruitgang wanneer het uiterlijk ZV is in vergelijking met MBV.</td></tr>
<tr><td rowspan="2">Jam spacing distance</td><td>↓</td><td>Kleinere afstand tussen de jams bij het volgen van een voertuig dat als ZV wordt weergegeven in vergelijking met MBV.</td></tr>
<tr><td>↓</td><td>Bij het volgen van een voertuig dat als ZV wordt weergegeven, wordt de afstand tussen de files verder kleiner wanneer bestuurders meer vertrouwen hebben in ZV's.</td></tr>
<tr><td>Comfortabele vertraging</td><td>↑</td><td>Bij het volgen van een voertuig dat als ZV verschijnt, grotere comfortabele vertraging wanneer bestuurders meer vertrouwen hebben in ZV's.</td></tr>
<tr><td>ZV-rijstijl</td><td>Gewenste snelheid</td><td>↓</td><td>Wanneer de rijstijl ZV is, is de gewenste snelheid kleiner voor bestuurders met een groter vertrouwen in ZV's.</td></tr>
<tr><td rowspan="3">Vertrouwen in ZV's</td><td>Gewenste snelheid</td><td>↓</td><td>Wanneer de rijstijl ZV is, is de gewenste snelheid kleiner voor bestuurders met een groter vertrouwen in ZV's.</td></tr>
<tr><td>Afstand tot jamafstand</td><td>↓</td><td>Bij het volgen van een voertuig dat als ZV wordt weergegeven, wordt de afstand tussen de files verder kleiner wanneer bestuurders meer vertrouwen hebben in ZV's.</td></tr>
<tr><td>Comfortabele vertraging</td><td>↑</td><td>Bij het volgen van een voertuig dat als ZV verschijnt, grotere comfortabele vertraging wanneer bestuurders meer vertrouwen hebben in ZV's.</td></tr>
<tr><td>INHALEN</td><td>ZV-uitstraling</td><td>Voorsprong na inhalen</td><td>↓</td><td>Kleinere doorvaarthoogte na het inhalen van een herkenbare ZV in vergelijking met MBV.</td><td>Gecontroleerde veldtest</td><td>2</td></tr>
</table>

Tabel S 2: Overzicht van de effecten van gemengde verkeersfactoren op het gap-acceptatiegedrag van menselijke bestuurders en verkeersefficiëntie.

Gedrag	Factor	Indicator	Effect		Studie	Hoofdstuk
GAP-ACCEPTATIE	**ZV-uitstraling**	**Geaccepteerde gap-grootte**	↑	Grootste geaccepteerde gap wanneer ZV's herkenbaar waren, met minder defensieve rijstijl en invoegen voor een ZV.	Rijsimulator	4
		Kritieke gap	↓	Kleinere kritieke gap wanneer het uiterlijk ZV is in vergelijking met MBV.	Gecontroleerde veldtest	2
			↓	Wanneer ZV's niet herkenbaar zijn, zijn kritieke gaps aanzienlijk kleiner wanneer ZV's minder defensief waren in vergelijking met meer defensief.	Rijsimulator	4
			↑	Maar als ze herkenbaar zijn, zijn kritieke gaps aanzienlijk groter wanneer ZV's minder defensief waren in vergelijking met meer defensief (bij het invoegen voor ZV).		
	ZV-rijstijl	**Geaccepteerde gap-grootte**	↑	Grootste geaccepteerde gap wanneer ZV's herkenbaar waren, met minder defensieve rijstijl en invoegen voor een ZV.		
		Kritieke gap	↑	Wanneer ZV's herkenbaar zijn, zijn kritieke gaps aanzienlijk groter wanneer ZV's minder defensief waren in vergelijking met meer defensief (bij het invoegen voor ZV).		
			↓	Wanneer ZV's niet herkenbaar zijn, zijn kritieke gaps aanzienlijk kleiner wanneer ZV's minder defensief waren in vergelijking met meer defensief.		
	Vertrouwen in ZV'S	**Kritieke gap**	↓	Het verstrekken van positieve informatie over ZV's (het vergroten van het vertrouwen) verkleint de kritieke gap verder.	Gecontroleerde veldtest	2
VERKEERS-EFFICIËNTIE OP T-VOORRANGSKRUISING	**ZV-uitstraling**	**Vertraging voor kleine-weg voertuigen**	↑	Toen ZV's minder defensief waren, grotere vertragingen voor kleine-weg voertuigen wanneer ZV's herkenbaar waren in vergelijking met niet-herkenbaar.	Microsimulatie	5
	ZV-rijstijl	**Vertraging voor kleine-weg voertuigen**	↑	De toename van de vertraging met ZV-penetratiegraad is groter wanneer de hoofdweg meer defensieve ZV's heeft in vergelijking met wanneer deze minder defensieve ZV's heeft.		
			↑	Bij een hogere penetratiegraad is de vertraging voor kleine-weg voertuigen groter wanneer ZV's defensiever zijn in vergelijking met wanneer ZV's herkenbaar en minder defensief zijn.		
		Lengte wachtrij	↑	De langste wachtrij werd waargenomen in 75% ZV-penetratiegraad met meer defensieve ZV's (gedragsaanpassing niet meegenomen); en de kortste wachtrijlengte werd waargenomen in conventioneel (volledig MBV) verkeer.		
	ZV-penetratiegraad	**Vertraging voor kleine-weg voertuigen**	↑	Toename van de ZV-penetratiegraad verhoogde vertraging voor kleine-weg voertuigen.		
		Lengte wachtrij	↑	De langste wachtrij werd waargenomen in 75% ZV-penetratiegraad met meer defensieve ZV's (gedragsaanpassing niet meegenomen); en de kortste wachtrijlengte werd waargenomen in conventioneel (volledig MBV) verkeer.		
	Gedragsaanpassing meenemen	**Vertraging voor kleine-weg voertuigen**	↑	In minder defensief ZV-verkeer leidt het overwegen van gedragsaanpassing tot een toename van de vertraging per klein-weg voertuig tot 75% (bij een penetratiegraad van 75%).		

2. **Het niet in overweging nemen van gedragsaanpassing van MBV's bij het voorspellen van de verkeersefficiëntie van gemengd verkeer kan tot onnauwkeurige resultaten leiden**. De microsimulatiestudie toont bijvoorbeeld aan dat het niet in aanmerking nemen van gedragsaanpassingen van MBV's bij gap-acceptatie zou kunnen leiden tot een onderschatting van de vertraging van kleine wegvoertuigen met ongeveer 75% (bij een ZV-penetratiegraad van 75%).
3. **Er is een sterkere neiging tot gedragsaanpassingen in het voorwaartse gezichtsveld van ZV's**. Interacties in het voorwaartse gezichtsveld van ZV's kunnen bestaan uit het uitvoeren van gap-acceptatie voor een ZV vanuit stilstand of het invoegen voor een ZV na het inhalen. In de praktijktest waren bestuurders bijvoorbeeld bereid op kortere afstanden in te voegen voor ZV's dan voor MBV's. Ook voegden ze dichter voor ZV's in nadat ze ze hadden ingehaald, in vergelijking met MBV's. Gedragsaanpassingen kunnen nog steeds optreden in andere gedragingen en richtingen, alleen kan de omvang kleiner zijn dan in het voorwaartse gezichtsveld. In een experiment met een rijsimulator vonden we ook gedragsaanpassing bij het volgen van auto's, waarbij bestuurders een kleinere gewenste stilstandsafstand (file) hadden bij het volgen van een ZV in vergelijking met een MBV.
4. **Als bestuurders een voertuig niet herkennen als een ZV, hebben bestuurders de neiging om het rijgedrag van het voertuig na te bootsen**. In een experiment met een rijsimulator ontdekten we bijvoorbeeld dat bestuurders grotere gaten accepteerden tijdens gap-acceptatie wanneer de (niet-herkenbare) ZV's defensiever reden en kleinere gaten accepteerden wanneer de (niet-herkenbare) ZV's minder defensief reden.
5. **Als bestuurders een voertuig herkennen als een ZV, dan zijn de richting en omvang van de gedragsaanpassingen afhankelijk van de mate van vertrouwen die bestuurders hebben in ZV's**. In een rijsimulatorexperiment ontdekten we bijvoorbeeld dat bestuurders kleinere gaten accepteerden tijdens het accepteren van gaten wanneer de (herkenbare) ZV's defensiever reden en grotere gaten accepteerden wanneer de (herkenbare) ZV's minder defensief reden. In de praktijktest, toen positieve informatie (vertrouwenwekkend) over ZV's werd verstrekt aan bestuurders, voegden ze na het inhalen nog dichter voor ZV's in.

Praktische implicaties en toekomstige onderzoeksrichtingen

De resultaten van dit proefschrift hebben implicaties voor verschillende stakeholders. **Bestuurders van door mensen bestuurde voertuigen** moeten zich bewust worden van de gedragsaanpassingen die ze kunnen ondergaan. **ZV-gebruikers** moeten zich ook bewust zijn van hoe andere bestuurders hun gedrag kunnen veranderen wanneer ze met hen omgaan. **Wegbeheerders** moeten een evaluatie maken van hoe zinvol/significant de effecten van gedragsaanpassing zijn, en wat voor soort verkeersmanagement en infrastructurele maatregelen ze kunnen nemen. **Autoriteiten voor rijbewijzen en voertuigvergunningen** moeten ook richtlijnen opstellen over ZV-aspecten zoals hun uiterlijk en rijstijl, en menselijke bestuurders opleiden om de effecten van gedragsaanpassing beter te beheersen. **Fabrikanten van ZV-auto's** moeten de effecten van hun voertuigen en systemen (uiterlijk en gedrag) op het overige wegverkeer onderzoeken. Ook zouden ZV-fabrikanten de gebruikers bewust kunnen maken van de gevolgen van de verschillende instellingen in de auto voor het omringende verkeer. ZV-gebruikers kunnen bijvoorbeeld worden geïnformeerd dat het behouden van defensieve instellingen (zoals een grote tijdsdruk) in adaptieve cruisecontrol ertoe kan leiden dat andere bestuurders dichterbij invoegen voor de ZV's. Idealiteris een nauwe samenwerking tussen alle stakeholders nodig om veilige en comfortabele rijomstandigheden te garanderen.

Naast de praktische implicaties geeft dit proefschrift richting voor toekomstig onderzoek. Gedragsaanpassingen in andere situaties (bijv. snelwegen, stedelijke wegen) en rijmanoeuvres (bijv. rijstrookwissel, noodremmen) moeten worden onderzocht. Effecten op gedragsaanpassing op de lange termijn zijn ook belangrijk om te worden bestudeerd, aangezien gedrag dat op korte termijn wordt waargenomen, heel anders kan zijn dan op de lange termijn. Een andere interessante onderzoeksrichting is de impact van eHMI's (external Human Machine Interfaces) van ZV's op de interacties met MBV's. Het is ook belangrijk om de interacties en effecten te onderzoeken in gemengd verkeer met verschillende penetratiegraden van ZV's. Een ander cruciaal aspect zijn de implicaties voor de verkeersveiligheid, die moeten worden bestudeerd. Ten slotte moet de consequentie van het overwegen van gedragsaanpassing op de gemeten macroscopische effecten op de verkeersefficiëntie verder worden onderzocht. Dit onderwerp is nog niet bestudeerd, behalve in dit proefschrift.

ಸಾರಾಂಶ (Language - Kannada)

ಪರಿಚಯ

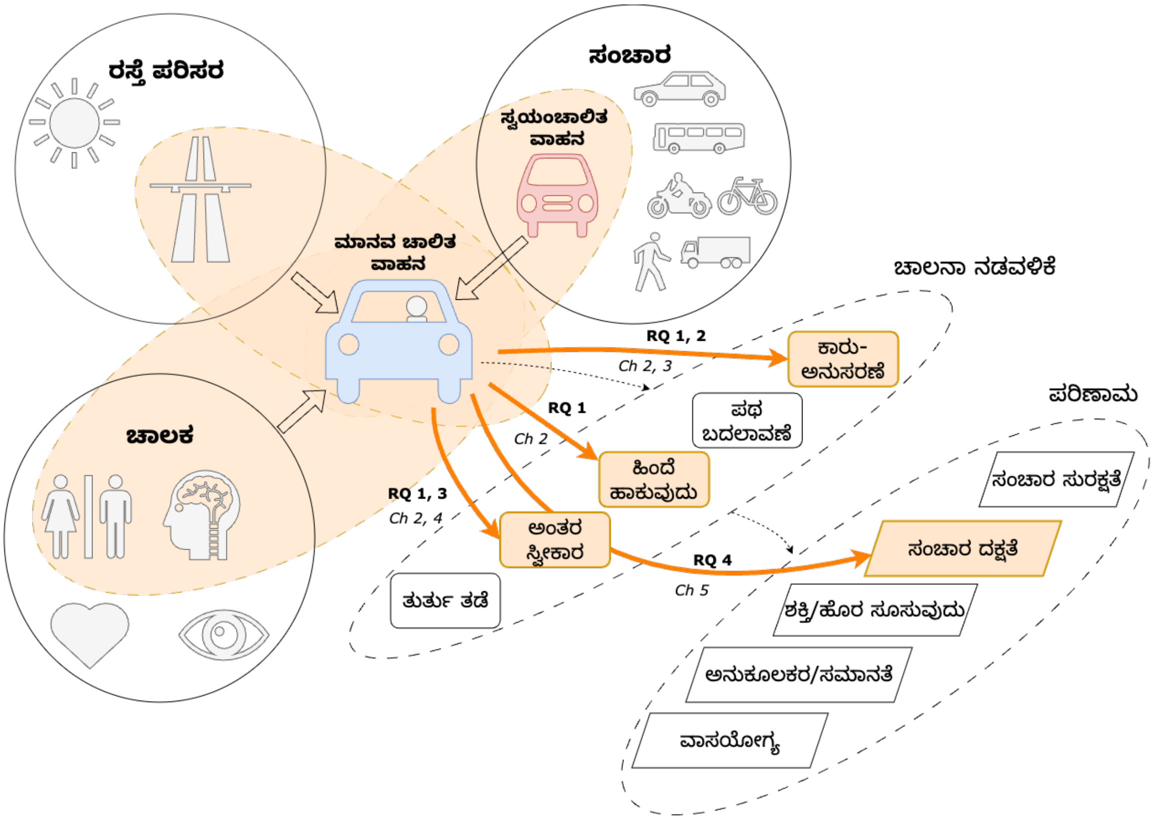
(ಭಾಗಶಃ) ಸ್ವಯಂಚಾಲಿತ ವಾಹನಗಳು (ಎವಿಗಳು) ಸಾರ್ವಜನಿಕ ರಸ್ತೆಗಳಲ್ಲಿ ಹೆಚ್ಚು ಪ್ರಚಲಿತವಾಗುತ್ತಿದ್ದಂತೆ, ಮಿಶ್ರ ಸಂಚಾರದಲ್ಲಿ (ಎವಿಗಳು ಮತ್ತು ಮಾನವ ಚಾಲಿತ ವಾಹನಗಳಿಂದ ಕೂಡಿದ ಸಂಚಾರ) ಅವುಗಳ ಏಕೀಕರಣದ ಬಗ್ಗೆ ಮತ್ತು ಸಂಚಾರ ಹರಿವು, ಸಂಚಾರ ಸುರಕ್ಷತೆ ಮತ್ತು ರಸ್ತೆ ಮೂಲಸೌಕರ್ಯದ ಮೇಲೆ ಅವು ಬೀರಬಹುದಾದ ಪರಿಣಾಮಗಳ ಬಗ್ಗೆಯೂ ಗಮನ ಹೆಚ್ಚುತ್ತಿದೆ. ಇಲ್ಲಿಯವರೆಗೆ ತುಲನಾತ್ಮಕವಾಗಿ ಕಡಿಮೆ ಗಮನವನ್ನು ಪಡೆದ ಒಂದು ಅಂಶವೆಂದರೆ ಮಿಶ್ರ ಸಂಚಾರದಲ್ಲಿ ಮಾನವ ಚಾಲಿತ ವಾಹನಗಳ (ಎಚ್ಡಿವಿ) ಚಾಲನಾ ನಡವಳಿಕೆಯ ಮೇಲೆ ಎವಿಗಳ ಪರಿಣಾಮ. ಎಚ್ಡಿವಿಗಳೊಂದಿಗಿನ ಎವಿಗಳ ಪರಸ್ಪರ ಕ್ರಿಯೆಗಳು ಇತರ ಎಚ್ಡಿವಿಗಳೊಂದಿಗಿನ ಎಚ್ಡಿವಿಗಳ ಪರಸ್ಪರ ಕ್ರಿಯೆಗಳಿಗಿಂತ ಭಿನ್ನವಾಗಿರಬಹುದು. ಇತ್ತೀಚೆಗೆ, ಇದನ್ನು ಬೆಂಬಲಿಸುವ ವೈಜ್ಞಾನಿಕ ಮಾಹಿತಿ ಹೆಚ್ಚುತ್ತಿರುವ ಪುರಾವೆಗಳು ಹೊರಹೊಮ್ಮಿವೆ. ಅಂತಹ ಬದಲಾವಣೆಗಳಲ್ಲಿ ಎಚ್ಡಿವಿಗಳು ಎವಿಗಳ ಹಿಂದೆ ಹಿಂಬಾಲಿಸುವಾಗ ಹತ್ತಿರದಿಂದ ಚಾಲನೆ ಮಾಡುವುದು ಅಥವಾ ಮಿಶ್ರ ಸಂಚಾರದಲ್ಲಿ ಚಾಲನೆ ಮಾಡುವಾಗ ಆಗಾಗ್ಗೆ ಪಥ ಬದಲಾವಣೆಗಳನ್ನು ಮಾಡುವುದು ಸೇರಿವೆ. ಈ ಬದಲಾವಣೆಗಳು ಒಟ್ಟಾರೆ ಸಂಚಾರ ಸುರಕ್ಷತೆ ಮತ್ತು ದಕ್ಷತೆಯ ಮೇಲೆ ನಕಾರಾತ್ಮಕ ಅಥವಾ ಸಕಾರಾತ್ಮಕ ಪರಿಣಾಮಗಳನ್ನು ಬೀರಬಹುದು. ಪ್ರಸ್ತುತ, ಯಾವ ಮಿಶ್ರ ಸಂಚಾರ ಅಂಶಗಳು ಎಚ್ಡಿವಿಗಳ ಚಾಲನಾ ನಡವಳಿಕೆಯ ಮೇಲೆ ಪರಿಣಾಮ ಬೀರುತ್ತವೆ ಮತ್ತು ಅವುಗಳ ಪರಿಣಾಮಗಳ ಸ್ವರೂಪದ ಬಗ್ಗೆ ಸೀಮಿತ ತಿಳುವಳಿಕೆ ಇದೆ. ಆದ್ದರಿಂದ, ಈ ಪ್ರಬಂಧವು ಎಚ್ಡಿವಿ ಚಾಲನಾ ನಡವಳಿಕೆಯಲ್ಲಿ ಯಾವುದೇ ಸಂಭಾವ್ಯ ಬದಲಾವಣೆಗಳ ಬಗ್ಗೆ ಉತ್ತಮ ಮತ್ತು ಆಳವಾದ ತಿಳುವಳಿಕೆಯನ್ನು ಪಡೆಯಲು ಎಚ್ಡಿವಿಗಳ ನಡವಳಿಕೆಯ ಮೇಲೆ

ಎವಿಗಳ ಪರಿಣಾಮಗಳನ್ನು ಅಧ್ಯಯನ ಮಾಡುವತ್ತ ಕೇಂದ್ರೀಕರಿಸಿದೆ, ಇದನ್ನು ಈ ಪ್ರಬಂಧದಲ್ಲಿ ನಡವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಗಳು ಎಂದು ಉಲ್ಲೇಖಿಸಲಾಗಿದೆ. ಈ ಪ್ರಬಂಧದ ಮುಖ್ಯ ಸಂಶೋಧನಾ ಪ್ರಶ್ನೆಯೆಂದರೆ:

ಮಾನವ ಚಾಲಿತ ವಾಹನಗಳ ಚಾಲನಾ ನಡವಳಿಕೆಯ ಮೇಲೆ ಸ್ವಯಂಚಾಲಿತ ವಾಹನಗಳ ಪರಿಣಾಮಗಳು ಯಾವುವು, ಮತ್ತು ಮಿಶ್ರ ಸಂಚಾರ ದಕ್ಷತೆಯ ಮೇಲೆ ಅವುಗಳ ಪರಿಣಾಮಗಳು ಯಾವುವು?

ಚಿತ್ರ 1 ಇದು ಈ ಪ್ರಬಂಧದ ವ್ಯಾಪ್ತಿಯ ಚಿತ್ರಣವಾಗಿದೆ, ಇದನ್ನು ಕಿತ್ತಳೆ ಛಾಯೆಯಿಂದ ಎತ್ತಿ ತೋರಿಸಲಾಗಿದೆ. ಇದು ಎಚ್ಡಿವಿಯನ್ನು ಕೇಂದ್ರದಲ್ಲಿ ಇರಿಸುತ್ತದೆ, ಇದು ಮೂರು ವಿಭಿನ್ನ ಅಂಶಗಳಿಂದ ಪ್ರಭಾವಿತವಾಗಿರುತ್ತದೆ: ರಸ್ತೆ ಪರಿಸರ (ಉದಾಹರಣೆಗೆ, ಹವಾಮಾನ, ಮೂಲಸೌಕರ್ಯ), ಸಂಚಾರ (ಇತರ ರಸ್ತೆ ಬಳಕೆದಾರರು) ಮತ್ತು ಚಾಲಕ (ವೈಯಕ್ತಿಕ ಗುಣಲಕ್ಷಣಗಳು). ಈ ಅಂಶಗಳು ಎಚ್ಡಿವಿಗಳ ಚಾಲನಾ ನಡವಳಿಕೆಯ ಮೇಲೆ ಪರಿಣಾಮ ಬೀರುತ್ತವೆ, ಉದಾಹರಣೆಗೆ ಕಾರು-ಅನುಸರಣೆ ಮತ್ತು ಅಂತರ ಸ್ವೀಕಾರ, ಇದು ಅಂತಿಮವಾಗಿ ಒಟ್ಟಾರೆ ಸಂಚಾರ ಸುರಕ್ಷತೆ ಮತ್ತು ದಕ್ಷತೆಯ ಮೇಲೆ ಪ್ರಭಾವ ಬೀರುತ್ತದೆ. ಈ ಪ್ರಬಂಧದಲ್ಲಿ, ನಾನು ಕಾರು-ಅನುಸರಣೆ, ಹಿಂದೆ ಹಾಕುವುದು ("ಓವರ್ಟೇಕಿಂಗ್") ಮತ್ತು ಅಂತರ ಸ್ವೀಕಾರ ನಡವಳಿಕೆ ಮತ್ತು ಸಂಚಾರ ದಕ್ಷತೆಯ ಮೇಲೆ ಅಂತರ ಸ್ವೀಕಾರದ ಪರಿಣಾಮದ ಮೇಲೆ ಕೇಂದ್ರೀಕರಿಸಿದೆ. ಸಂಚಾರ ಎಂಜಿನಿಯರಿಂಗ್ನಲ್ಲಿ ಚಾಲನಾ ನಡವಳಿಕೆಯನ್ನು ಸಾಮಾನ್ಯವಾಗಿ ಹೇಗೆ ನಿರೂಪಿಸಲಾಗುತ್ತದೆ ಮತ್ತು ಅಧ್ಯಯನ ಮಾಡಲಾಗುತ್ತದೆ ಎಂಬುದರ ಆಧಾರದ ಮೇಲೆ ಇವುಗಳನ್ನು ಭಾಗಶಃ ಆಯ್ಕೆ ಮಾಡಲಾಗಿದೆ, ಇದು ನೀರ ಚಾಲನೆ (ಕಾರು-ಅನುಸರಣೆ) ಮತ್ತು ಕೋಣಾಂಶ ಚಾಲನೆ (ಹಿಂದೆ ಹಾಕುವುದು ಮತ್ತು ಅಂತರ ಸ್ವೀಕಾರ) ನಡವಳಿಕೆಗಳನ್ನು ಒಳಗೊಂಡಿದೆ; ಮತ್ತು ಭಾಗಶಃ ಈ ಸಂಶೋಧನೆಯ ಸಮಯದಲ್ಲಿ ಪಡೆದ ಒಳನೋಟಗಳ ಮೇಲೆ. ಸಂಚಾರ ದಕ್ಷತೆಯ ಮೇಲಿನ ಪರಿಣಾಮವನ್ನು ಅಧ್ಯಯನ ಮಾಡಲು ಅಂತರ ಸ್ವೀಕಾರ ನಡವಳಿಕೆಯನ್ನು ಆಯ್ಕೆ ಮಾಡಲಾಯಿತು ಏಕೆಂದರೆ ಇದು ಕೂಡು ರಸ್ತೆ ಮೇಲ್ಭಾಗದ ರಸ್ತೆ ಜಾಲದಲ್ಲಿ ಮತ್ತು ರಸ್ತೆಯಲ್ಲಿ ಸಂಚಾರವು ವಿಲೀನಗೊಳ್ಳುತ್ತಿರುವ ರಸ್ತೆಯ ಸಂಚಾರ ಹರಿವಿನ ಮೇಲೆ ಪರಿಣಾಮ ಬೀರುತ್ತದೆ. ಇದಲ್ಲದೆ, ಅಂತರ ಸ್ವೀಕಾರದ ಸಮಯದಲ್ಲಿ, ಚಾಲಕರು ಮುಂಬರುವ ವಾಹನಗಳನ್ನು ಗಮನಿಸಲು ಅವಕಾಶವನ್ನು ಹೊಂದಿರುತ್ತಾರೆ, ಬಹುಶಃ ಎವಿ ನೋಟದಂತಹ ಮಿಶ್ರ ಸಂಚಾರ ಅಂಶಗಳಿಗೆ ಹೆಚ್ಚು ಒಳಗಾಗುತ್ತಾರೆ. ಮುಖ್ಯ ಸಂಶೋಧನಾ ಪ್ರಶ್ನೆಗೆ ಉತ್ತರಿಸಲು, ಈ ಕೆಳಗಿನ ಉಪ ಸಂಶೋಧನಾ ಪ್ರಶ್ನೆಗಳನ್ನು ವ್ಯಾಖ್ಯಾನಿಸಲಾಗಿದೆ, ಅವುಗಳನ್ನು ಚಿತ್ರ 1 ರಲ್ಲಿ ದಪ್ಪ ಬಾಣಗಳಾಗಿ ಚಿತ್ರಿಸಲಾಗಿದೆ:

1. ಎವಿಗಳೊಂದಿಗಿನ ಸಂವಹನದ ಸಮಯದಲ್ಲಿ ಮಾನವ ಚಾಲಕರ ಸಂಭಾವ್ಯ ನಡವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಗಳು ಯಾವುವು?
2. ಎಚ್ಡಿವಿಗಳ ನಡವಳಿಕೆಯನ್ನು ಅನುಸರಿಸಿ ಕಾರಿನ ಮೇಲೆ ಎವಿಗಳ ಪರಿಣಾಮವೇನು?
3. ಆದ್ಯತೆಯ ಟಿ-ಕೂಡು ರಸ್ತೆ ಗಳಲ್ಲಿ ಮಿಶ್ರ (ಸ್ವಯಂಚಾಲಿತ ಮತ್ತು ಮಾನವ ಚಾಲಿತ) ಸಂಚಾರದಲ್ಲಿ ಮಾನವ ಚಾಲಕರು ಅಂತರ ಸ್ವೀಕಾರ ತಂತ್ರಗಳನ್ನು ಹೇಗೆ ನಿರ್ವಹಿಸುತ್ತಾರೆ?
4. ಮಿಶ್ರ ಸಂಚಾರವು ಆದ್ಯತೆಯ ಟಿ-ಕೂಡು ರಸ್ತೆಗಳ ಸಂಚಾರ ದಕ್ಷತೆಯ ಮೇಲೆ ಹೇಗೆ ಪರಿಣಾಮ ಬೀರುತ್ತದೆ?



ಚಿತ್ರ 1: ಈ ಪ್ರಬಂಧದ ರೂಪುರೇಷೆಯಾಗಿ ಪರಿಕಲ್ಪನಾ ಚೌಕಟ್ಟು

ವಿಧಾನಗಳು

ಸಂಶೋಧನಾ ಪ್ರಶ್ನೆಗಳಿಗೆ ಉತ್ತರಿಸಲು, ಈ ಪ್ರಬಂಧವು ಚಾಲನಾ "ಸಿಮ್ಯುಲೇಟರ್ಗಳು" ಮತ್ತು ಕ್ಷೇತ್ರ ಪರೀಕ್ಷೆಗಳಂತಹ ಪ್ರಾಯೋಗಿಕ ದತ್ತಾಂಶ ಸಂಗ್ರಹ ವಿಧಾನಗಳನ್ನು ಅಳವಡಿಸಿಕೊಂಡಿತು. ಎವಿಗಳು ಪ್ರಸ್ತುತ ಸಾರ್ವಜನಿಕ ರಸ್ತೆಗಳಲ್ಲಿ ವ್ಯಾಪಕವಾಗಿ ಕಾರ್ಯನಿರ್ವಹಿಸದ ಕಾರಣ, ಮತ್ತು ಎವಿಗಳು ಮತ್ತು ಎಚ್ಡಿವಿಗಳ ನಡುವಿನ ಪರಸ್ಪರ ಕ್ರಿಯೆಗಳ ಬಗ್ಗೆ ಬಹಳ ಸೀಮಿತ ಮಾಹಿತಿ ಲಭ್ಯವಿರುವುದರಿಂದ, ಈ ಪ್ರಬಂಧಕ್ಕಾಗಿ ಮಾಹಿತಿ ಸಂಗ್ರಹಣೆ ಪ್ರಯತ್ನಗಳನ್ನು ಮಾಡಲಾಯಿತು. ಚಾಲನಾ ಸಿಮ್ಯುಲೇಟರ್ ಗಳು ಸುರಕ್ಷಿತ ಮತ್ತು ನಿಯಂತ್ರಿತ ಆನ್ಲೈನ್ ಪರಿಸರದಲ್ಲಿ ಚಾಲಕರ ನಡವಳಿಕೆಯನ್ನು ಪ್ರಾಯೋಗಿಕವಾಗಿ ಅಧ್ಯಯನ ಮಾಡಲು ಸಹಾಯ ಮಾಡುತ್ತದೆ, ಅಲ್ಲಿ ವಿಭಿನ್ನ ಸಂಚಾರ ಪರಿಸ್ಥಿತಿಗಳನ್ನು ವೆಚ್ಚ-ಪರಿಣಾಮಕಾರಿ ರೀತಿಯಲ್ಲಿ ಪರೀಕ್ಷಿಸಬಹುದು. ಕ್ಷೇತ್ರ ಪರೀಕ್ಷೆಗಳು ನಿಜ ಜೀವನದ ಸನ್ನಿವೇಶದಲ್ಲಿ ಚಾಲನಾ ನಡವಳಿಕೆಯ ತನಿಖೆಯನ್ನು ಅನುಮತಿಸುತ್ತವೆ, ಆದ್ದರಿಂದ ಚಾಲನಾ ಸಿಮ್ಯುಲೇಟರ್ ಅಧ್ಯಯನಗಳಿಗಿಂತ ಹೆಚ್ಚಿನ ಸಿಂಧುತ್ವವನ್ನು ಹೊಂದಿವೆ, ಆದಾಗ್ಯೂ ಚಾಲನಾ ಸಿಮ್ಯುಲೇಟರ್ಗಳಿಗೆ ಹೋಲಿಸಿದರೆ ಪರಿಸರ ಪರಿಸ್ಥಿತಿಗಳನ್ನು ನಿಯಂತ್ರಿಸಲು ಕಡಿಮೆ ಸಾಧ್ಯತೆಗಳನ್ನು ಹೊಂದಿವೆ. ಆದ್ದರಿಂದ, ಈ ಪ್ರಬಂಧವು ಈ ಎರಡು ವಿಧಾನಗಳ ಸಂಯೋಜನೆಯನ್ನು ಬಳಸಿತು.

ಈ ಪ್ರಬಂಧವು ಮುಖ್ಯ ಚಾಲನಾ ನಡವಳಿಕೆಗಳ ಗಣಿತಶಾಸ್ತ್ರದ ಅನುಕರಣೆಯನ್ನು ಸಹ ಒಳಗೊಂಡಿದೆ. ಉದಾಹರಣೆಗೆ, ಚಾಲನಾ ಸಿಮ್ಯುಲೇಟರ್ ಪ್ರಯೋಗಗಳಿಂದ ಸಂಗ್ರಹಿಸಿದ ಪ್ರಾಯೋಗಿಕ ಮಾಹಿತಿಯನ್ನು ಬಳಸಿಕೊಂಡು ಕಾರು ಅನುಸರಿಸುವ ನಡವಳಿಕೆ ಮತ್ತು ಅಂತರ ಸ್ವೀಕಾರ ನಡವಳಿಕೆಯ ಗಣಿತದ ಮಾದರಿಗಳನ್ನು

ಅಂದಾಜಿಸಲಾಗಿದೆ. ಈ ಮಾದರಿಗಳು ಎಚ್ಡಿವಿಗಳ ನಡವಳಿಕೆಗಳನ್ನು ವ್ಯಾಖ್ಯಾನಿಸಲು, ಮಿಶ್ರ ಸಂಚಾರದಲ್ಲಿ ಸಂಚಾರ ದಕ್ಷತೆಯ "ಮ್ಯಾಕ್ರೋಸ್ಕೋಪಿಕ್" ಸೂಚಕಗಳನ್ನು ಅಧ್ಯಯನ ಮಾಡಲು "ಮೈಕ್ರೋಸಿಮ್ಯುಲೇಶನ್" ನಲ್ಲಿದ್ದವು.

ಫಲಿತಾಂಶಗಳು

ಮುಖ್ಯ ಸಂಶೋಧನೆಗಳನ್ನು ಕೋಷ್ಟಕ ಮೇಜು 1 ರಲ್ಲಿ ಸಂಕ್ಷಿಪ್ತಗೊಳಿಸಲಾಗಿದೆ. ನಿರ್ದಿಷ್ಟ ಮಿಶ್ರ ಸಂಚಾರ ಅಂಶಗಳಿಂದ ಮಾನವ ಚಾಲಕರ ವಿಭಿನ್ನ ನಡವಳಿಕೆಗಳು ಹೇಗೆ ಪರಿಣಾಮ ಬೀರುತ್ತವೆ ಎಂಬುದನ್ನು ಕೋಷ್ಟಕ ತೋರಿಸುತ್ತದೆ. ಚಾಲನಾ ನಡವಳಿಕೆಗಳನ್ನು ಕೆಲವು ಸೂಚಕಗಳು ಮತ್ತು ಪರಿಣಾಮದ ನಿರ್ದಿಷ್ಟ ಸ್ವರೂಪದಿಂದ ಪ್ರತಿನಿಧಿಸಲಾಗುತ್ತದೆ. ಈ ಪ್ರಬಂಧದ ಯಾವ ಅಧ್ಯಯನ ಮತ್ತು ಅಧ್ಯಾಯಕ್ಕೆ ಸಂಬಂಧಿಸಿದೆ ಎಂಬುದನ್ನು ಸಹ ಇದು ತೋರಿಸುತ್ತದೆ.

ಮಿಶ್ರ ಸಂಚಾರಕ್ಕೆ ಸಂಬಂಧಿಸಿದ ಅಂಶಗಳು ಎಚ್ಡಿವಿ ನಡವಳಿಕೆ ಮತ್ತು ನಡವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಯ ಮೇಲೆ ಹಲವಾರು ಪರಿಣಾಮಗಳನ್ನು ಬೀರುತ್ತವೆ ಎಂದು ಗಮನಿಸಲಾಗಿದೆ. ನಿರ್ದಿಷ್ಟವಾಗಿ, ನಾನು ಈ ಕೆಳಗಿನ ಮಿಶ್ರ ಸಂಚಾರ ಅಂಶಗಳ ಮೇಲೆ ಕೇಂದ್ರೀಕರಿಸಿದ್ದೆ: ಎವಿ ನೋಟ, ಎವಿ ಚಾಲನಾ ಶೈಲಿ, ಎವಿಗಳಲ್ಲಿ ನಂಬಿಕೆ ಮತ್ತು ಎವಿ ನುಗ್ಗುವ ದರ. ಎಚ್ಡಿವಿಗಳ ಕಾರು-ಅನುಸರಿಸುವ ನಡವಳಿಕೆ, ಅಂತರ ಸ್ವೀಕಾರ ನಡವಳಿಕೆ ಮತ್ತು ಹಿಂದೆ ಹಾಕುವ ನಡವಳಿಕೆ ಸೇರಿದಂತೆ ಎಚ್ಡಿವಿಗಳ ಮೂಲಭೂತ ಚಾಲನಾ ತಂತ್ರಗಳ ಮೇಲೆ ಅವುಗಳ ಪರಿಣಾಮಗಳನ್ನು ನಾನು ತನಿಖೆ ಮಾಡಿದ್ದೆ. ಆದ್ಯತೆಯ ಟಿ-ಕೂಡು ರಸ್ತೆಗಳಲ್ಲಿ ಸಂಚಾರ ದಕ್ಷತೆಯ ಮೇಲೆ ಅಂತರ-ಸ್ವೀಕಾರ ನಡವಳಿಕೆಯಲ್ಲಿನ ಬದಲಾವಣೆಗಳ ಪರಿಣಾಮವನ್ನು ನಾನು ತನಿಖೆ ಮಾಡಿದೆ. ಮೇಜು 1 ರಲ್ಲಿ ತೋರಿಸಿರುವಂತೆ ಈ ನಡವಳಿಕೆಗಳನ್ನು ವಿಭಿನ್ನ ಸೂಚಕಗಳನ್ನು ಬಳಸಿಕೊಂಡು ಅಳೆಯಲಾಗಿದೆ, ಅಲ್ಲಿ ಈ ಸೂಚಕಗಳ ಮೇಲಿನ ಪರಿಣಾಮಗಳ ನಿರ್ದಿಷ್ಟ ದಿಕ್ಕುಗಳನ್ನು ಸಹ ಪ್ರಸ್ತುತಪಡಿಸಲಾಗಿದೆ.

ಈ ಪ್ರಬಂಧದ ನಿರ್ದಿಷ್ಟ ಫಲಿತಾಂಶಗಳ ಜೊತೆಗೆ, ಎಲ್ಲಾ ಸಂಶೋಧನೆಗಳ ಸಂಯೋಜನೆ ಮತ್ತು ಚರ್ಚೆಯಿಂದ ಈ ಕೆಳಗಿನ ಪ್ರಮುಖ ಅಂಶಗಳು ಸಹ ಉಂಟಾಗುತ್ತವೆ:

1. **ಮಿಶ್ರ ಸಂಚಾರ ಅಂಶಗಳು ಮಾನವ ಚಾಲಕರ ನಡವಳಿಕೆಗಳ ಮೇಲೆ ಪರಿಣಾಮ ಬೀರುತ್ತವೆ, ಮತ್ತು ಇದು ಮ್ಯಾಕ್ರೋಸ್ಕೋಪಿಕ್ ಮಟ್ಟದಲ್ಲಿ ಸಂಚಾರ ದಕ್ಷತೆಯ ಮೇಲೆ ಪರಿಣಾಮ ಬೀರುತ್ತದೆ**. ಉದಾಹರಣೆಗೆ, ಡ್ರೈವಿಂಗ್ ಸಿಮ್ಯುಲೇಟರ್ ಪ್ರಯೋಗದಲ್ಲಿ, ಮಾನವ ಚಾಲಕರು ಕಡಿಮೆ ರಕ್ಷಣಾತ್ಮಕವಾಗಿ ಚಾಲನೆ ಮಾಡುತ್ತಿದ್ದ ಗುರುತಿಸಬಹುದಾದ ಎವಿ ಮುಂದೆ ವಿಲೀನಗೊಳ್ಳಬೇಕಾದಾಗ ಪ್ರಮುಖ ರಸ್ತೆ ಸಂಚಾರ ಪ್ರವಾಹದಲ್ಲಿ ದೊಡ್ಡ ಅಂತರಗಳನ್ನು ಒಪ್ಪಿಕೊಳ್ಳಲು ಒಲವು ತೋರಿದರು. ಮೈಕ್ರೋಸಿಮ್ಯುಲೇಶನ್ನಲ್ಲಿ ಎಚ್ಡಿವಿಗಳ ಅಂತರ ಸ್ವೀಕಾರ ನಡವಳಿಕೆಯನ್ನು ಜಾರಿಗೆ ತಂದ ನಂತರ, ಪ್ರಮುಖ ರಸ್ತೆ ಸಂಚಾರವು ಕಡಿಮೆ ರಕ್ಷಣಾತ್ಮಕ ಗುರುತಿಸಬಹುದಾದ ಎವಿಗಳನ್ನು ಹೊಂದಿರುವಾಗ ಸಣ್ಣ ರಸ್ತೆ ಎಚ್ಡಿವಿ ವಾಹನಗಳ ವಿಳಂಬವು ದೊಡ್ಡದಾಗಿದೆ ಎಂದು ಇದು ತೋರಿಸಿದೆ.

ಮೇಜು 1: ಮಾನವ ಚಾಲಕ ನಡವಳಿಕೆಯ ಮೇಲೆ ಮಿಶ್ರ ಸಂಚಾರ ಅಂಶಗಳ ಪರಿಣಾಮಗಳ ಅವಲೋಕನ

Behavior	Factor	Indicator	Effect		Study	Chapter
CAR-FOLLOWING	AV appearance	Desired velocity	↓	Smaller desired velocity when following vehicle appearing as AV compared to HDV.	Modelling using empirical data	3
		Safe time headway	↓	Smaller safe time headway when appearance is AV compared to HDV.		
		Jam spacing distance	↓	Smaller jam spacing distance when following vehicle appearing as AV compared to HDV.		
			↓	When following vehicle appearing as AV, jam spacing further reduces when drivers have higher trust in AVs		
		Comfortable deceleration	↑	When following vehicle appearing as AV, larger comfortable deceleration when drivers have higher trust in AVs		
	AV driving style	Desired velocity	↓	When driving style is AV, desired velocity smaller for drivers having higher trust in AVs.		
	Trust in AVs	Desired velocity	↓	When driving style is AV, desired velocity smaller for drivers having higher trust in AVs.		
		Jam spacing distance	↓	When following vehicle appearing as AV, jam spacing further reduces when drivers have higher trust in AVs		
		Comfortable deceleration	↑	When following vehicle appearing as AV, larger comfortable deceleration when drivers have higher trust in AVs		
OVERTAKING	AV appearance	Headway after overtaking	↓	Smaller headway after overtaking a recognisable AV compared to HDV.	Controlled field test	2
GAP ACCEPTANCE	AV appearance	Accepted gap size	↑	Largest accepted gap when AVs were recognizable, with less defensive driving style, and merging in front of an AV.	Driving simulator	4
		Critical gap	↓	Smaller critical gap when appearance is AV compared to HDV.	Controlled field test	2
			↓	When AVs are non-recognizable, critical gaps significantly smaller when AVs were less defensive compared to more defensive.	Driving simulator	4
			↑	But when recognizable, critical gaps significantly larger when AVs were less defensive compared to more defensive (when merging in front of AV).		
	AV driving style	Accepted gap size	↑	Largest accepted gap when AVs were recognizable, with less defensive driving style, and merging in front of an AV.		
		Critical gap	↑	When AVs are recognizable, critical gaps significantly larger when AVs were less defensive compared to more defensive (when merging in front of AV).		
			↓	When AVs are non-recognizable, critical gaps significantly smaller when AVs were less defensive compared to more defensive.		
	Trust in AVs	Critical gap	↓	Provision of positive information on AVs (increasing trust) reduces critical gap further.	Controlled field test	2
TRAFFIC EFFICIENCY AT PRIORITY T-INTERSECTION	AV appearance	Delay for minor road vehicles	↑	When AVs were less defensive, larger delays for minor road vehicles when AVs were recognizable compared to being non-recognizable.	Microsimulation	5
	AV driving style	Delay for minor road vehicles	↑	Increase in delay with AV penetration rate is larger when the major road has More defensive AVs compared to when it has Less defensive AVs.		
			↑	At larger penetration rates, delay for minor road vehicles is larger when AVs are more defensive as compared to when AVs are recognizable and less defensive.		
		Queue length	↑	Longest queue was observed in 75% AV penetration rate traffic with more defensive AVs (behavioral adaptation not considered); and shortest queue length was observed in conventional (fully HDV) traffic.		
	AV penetration rate	Delay for minor road vehicles	↑	Increase in AV penetration rate increased delay for minor road vehicles.		
		Queue length	↑	Longest queue was observed in 75% AV penetration rate traffic with more defensive AVs (behavioral adaptation not considered); and shortest queue length was observed in conventional (fully HDV) traffic.		
	Considering Behavioral Adaptation	Delay for minor road vehicles	↑	In less defensive AV traffic, considering behavioral adaptation results in an increase in delay per minor road vehicle by up to 75% (at 75% penetration rate).		

This dissertation investigated the effects of several factors on different indicators. The above table only presents the effects that resulted in a (significant) change in the indicators, only for mixed traffic specific factors. The factors did not have any significant effect on the other indicators.

The complete list of factors considered in this dissertation were: Mixed traffic specific factors (AV appearance, AV driving style, trust in AVs, AV penetration rate, considering behavioral adaptation), general factors (Driver age, driver gender, driver driving style). The complete list of indicators investigated were: Car-following (Jam spacing, Desired velocity, Safe time headway, Maximum acceleration, Comfortable deceleration), Gap acceptance (Accepted gap size, Critical gap, probability of accepting a gap), Overtaking (Headway after overtaking, Lateral distance while overtaking), Traffic efficiency at priority T intersection(Delay per vehicle on minor road, Delay per vehicle on major road, Queue length)

2. **ಮಿಶ್ರ ಸಂಚಾರದ ಸಂಚಾರ ದಕ್ಷತೆಯನ್ನು ಊಹಿಸುವಾಗ ಎಚ್ಡಿವಿಗಳ ನಡವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಯನ್ನು ಪರಿಗಣಿಸದಿರುವುದು ತಪ್ಪಾದ ಫಲಿತಾಂಶಗಳಿಗೆ ಕಾರಣವಾಗಬಹುದು**. ಉದಾಹರಣೆಗೆ, ಅಂತರ ಸ್ವೀಕಾರದಲ್ಲಿ ಎಚ್ಡಿವಿಗಳ ನಡವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಗಳನ್ನು ಪರಿಗಣಿಸದಿರುವುದು ಸಣ್ಣ ರಸ್ತೆ ವಾಹನಗಳ ವಿಳಂಬವನ್ನು ಸುಮಾರು ೭೫% ರಷ್ಟು ಕಡಿಮೆ ಅಂದಾಜು ಮಾಡಲು ಕಾರಣವಾಗಬಹುದು (೭೫% ಎವಿ ನುಗ್ಗುವ ದರದಲ್ಲಿ).
3. **ಎವಿಗಳ ದೃಷ್ಟಿಕೋನದ ಫಾರ್ವರ್ಡ್ ಕ್ಷೇತ್ರದಲ್ಲಿ ನಡವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಗಳು ಸಂಭವಿಸುವ ಬಲವಾದ ಪ್ರವೃತ್ತಿ ಇದೆ**. ಎವಿಗಳ ದೃಷ್ಟಿಕೋನದ ಮುಂಭಾಗ ಕ್ಷೇತ್ರದಲ್ಲಿನ ಪರಸ್ಪರ ಕ್ರಿಯೆಗಳು ಎವಿಯ ಮುಂದೆ ನಿಲ್ಲದಂತೆ ಅಂತರ ಸ್ವೀಕಾರವನ್ನು ನಿರ್ವಹಿಸುವುದು ಅಥವಾ ಹಿಂದೆ ಹಾಕುವುದು ಮಾಡಿದ ನಂತರ ಎವಿ ಮುಂದೆ ವಿಲೀನಗೊಳ್ಳುವುದು. ಉದಾಹರಣೆಗೆ, ಕ್ಷೇತ್ರ ಪರೀಕ್ಷೆಯಲ್ಲಿ, ಚಾಲಕರು ಎಚ್ಡಿವಿಗಳ ಮುಂದೆ ಇರುವುದಕ್ಕಿಂತ ಹತ್ತಿರದಲ್ಲಿ ಎವಿಗಳ ಮುಂದೆ ವಿಲೀನಗೊಳ್ಳಲು ಸಿದ್ಧರಿದ್ದರು. ಅಲ್ಲದೆ, ಎಚ್ಡಿವಿಗಳಿಗೆ ಹೋಲಿಸಿದರೆ, ಅವುಗಳನ್ನು ಹಿಂದಿಕ್ಕಿದ ನಂತರ ಅವು ಎವಿಗಳ ಮುಂದೆ ಹತ್ತಿರವಾಗಿ ವಿಲೀನಗೊಂಡವು. ನಡವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಗಳು ಇನ್ನೂ ಇತರ ನಡವಳಿಕೆಗಳು ಮತ್ತು ದಿಕ್ಕುಗಳಲ್ಲಿ ಸಂಭವಿಸಬಹುದು, ಆದರೆ ಅದರ ವ್ಯಾಪ್ತಿಯ ಮಟ್ಟ ಫಾರ್ವರ್ಡ್ ಕ್ಷೇತ್ರಕ್ಕಿಂತ ಚಿಕ್ಕದಾಗಿರಬಹುದು. ಡ್ರೈವಿಂಗ್ ಸಿಮ್ಯುಲೇಟರ್ ಪ್ರಯೋಗದಲ್ಲಿ, ಎಚ್ಡಿವಿಗೆ ಹೋಲಿಸಿದರೆ ಎವಿಯನ್ನು ಅನುಸರಿಸುವಾಗ ಚಾಲಕರು ಕಡಿಮೆ ಅಪೇಕ್ಷಿತ ನಿಲುಗಡೆ (ಜಾಮ್) ದೂರವನ್ನು ಹೊಂದಿರುವ ಕಾರು-ಅನುಸರಣೆಯಲ್ಲಿ ನಡವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಯನ್ನು ನಾವು ಕಂಡುಕೊಂಡಿದ್ದೇವೆ.
4. **ಚಾಲಕರು ವಾಹನವನ್ನು ಎವಿ ಎಂದು ಗುರುತಿಸದಿದ್ದರೆ, ಚಾಲಕರು ವಾಹನದ ಚಾಲನಾ ನಡವಳಿಕೆಯನ್ನು ಅನುಕರಿಸುತ್ತಾರೆ**. ಉದಾಹರಣೆಗೆ, ಡ್ರೈವಿಂಗ್ ಸಿಮ್ಯುಲೇಟರ್ ಪ್ರಯೋಗದಲ್ಲಿ, (ಗುರುತಿಸಲಾಗದ) ಎವಿಗಳು ಹೆಚ್ಚು ರಕ್ಷಣಾತ್ಮಕವಾಗಿ ಚಾಲನೆ ಮಾಡಿದಾಗ ಚಾಲಕರು ಅಂತರ ಸ್ವೀಕಾರದ ಸಮಯದಲ್ಲಿ ದೊಡ್ಡ ಅಂತರಗಳನ್ನು ಒಪ್ಪಿಕೊಂಡರು ಮತ್ತು (ಗುರುತಿಸಲಾಗದ) ಎವಿಗಳು ಕಡಿಮೆ ರಕ್ಷಣಾತ್ಮಕವಾಗಿ ಚಾಲನೆ ಮಾಡಿದಾಗ ಸಣ್ಣ ಅಂತರಗಳನ್ನು ಒಪ್ಪಿಕೊಂಡರು ಎಂದು ನಾವು ಕಂಡುಕೊಂಡಿದ್ದೇವೆ.
5. **ಚಾಲಕರು ವಾಹನವನ್ನು ಎವಿ ಎಂದು ಗುರುತಿಸಿದರೆ, ನಡುವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಗಳ ದಿಕ್ಕು ಮತ್ತು ವ್ಯಾಪ್ತಿ ಚಾಲಕರು ಎವಿಗಳಲ್ಲಿ ಹೊಂದಿರುವ ವಿಶ್ವಾಸದ ಮಟ್ಟವನ್ನು ಅವಲಂಬಿಸಿರುತ್ತದೆ**. ಉದಾಹರಣೆಗೆ, ಡ್ರೈವಿಂಗ್ ಸಿಮ್ಯುಲೇಟರ್ ಪ್ರಯೋಗದಲ್ಲಿ, (ಗುರುತಿಸಬಹುದಾದ) ಎವಿಗಳು ಹೆಚ್ಚು ರಕ್ಷಣಾತ್ಮಕವಾಗಿ ಚಾಲನೆ ಮಾಡಿದಾಗ ಚಾಲಕರು ಅಂತರ ಸ್ವೀಕಾರದ ಸಮಯದಲ್ಲಿ ಸಣ್ಣ ಅಂತರಗಳನ್ನು ಒಪ್ಪಿಕೊಂಡರು ಮತ್ತು (ಗುರುತಿಸಬಹುದಾದ) ಎವಿಗಳು ಕಡಿಮೆ ರಕ್ಷಣಾತ್ಮಕವಾಗಿ ಚಾಲನೆ ಮಾಡಿದಾಗ ದೊಡ್ಡ ಅಂತರಗಳನ್ನು ಒಪ್ಪಿಕೊಂಡರು ಎಂದು ನಾವು ಕಂಡುಕೊಂಡಿದ್ದೇವೆ. ಕ್ಷೇತ್ರ ಪರೀಕ್ಷೆಯಲ್ಲಿ, ಚಾಲಕರಿಗೆ ಎವಿಗಳ ಬಗ್ಗೆ ಸಕಾರಾತ್ಮಕ ಮಾಹಿತಿಯನ್ನು (ವಿಶ್ವಾಸ-ನಿರ್ಮಾಣ) ಒದಗಿಸಿದಾಗ, ಓವರ್ಟೇಕ್ ಮಾಡಿದ ನಂತರ ಅವು ಎವಿಗಳ ಮುಂದೆ ಇನ್ನಷ್ಟು ಹತ್ತಿರಕ್ಕೆ ವಿಲೀನಗೊಂಡವು.

ಪ್ರಾಯೋಗಿಕ ಪರಿಣಾಮಗಳು ಮತ್ತು ಭವಿಷ್ಯದ ಸಂಶೋಧನಾ ನಿರ್ದೇಶನಗಳು

ಈ ಪ್ರಬಂಧದ ಫಲಿತಾಂಶಗಳು ಹಲವಾರು ವರ್ಗಗಳಿಗೆ ಪರಿಣಾಮಗಳನ್ನು ಬೀರುತ್ತದೆ. **ಹಸ್ತಚಾಲಿತ ವಾಹನಗಳ ಚಾಲಕರು** ಅವರು ಒಳಗಾಗಬಹುದಾದ ನಡವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಗಳ ಬಗ್ಗೆ ತಿಳಿದಿರಬೇಕು. **ಎವಿ ಬಳಕೆದಾರರು** ಇತರ ಚಾಲಕರು ಅವರೊಂದಿಗೆ ಸಂವಹನ ನಡೆಸುವಾಗ ತಮ್ಮ ನಡವಳಿಕೆಯನ್ನು ಹೇಗೆ ಬದಲಾಯಿಸಬಹುದು ಎಂಬುದರ ಬಗ್ಗೆಯೂ ಜಾಗೃತರಾಗಿರಬೇಕು. **ನಡವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಯ ಪರಿಣಾಮಗಳು ಎಷ್ಟು ಅರ್ಥಪೂರ್ಣ / ಮಹತ್ವದ್ದಾಗಿವೆ ಮತ್ತು ಅವರು ಯಾವ ರೀತಿಯ ಸಂಚಾರ ನಿರ್ವಹಣೆ ಮತ್ತು ಮೂಲಸೌಕರ್ಯ ಕ್ರಮಗಳನ್ನು ತೆಗೆದುಕೊಳ್ಳಬಹುದು** ಎಂಬುದರ ಮೌಲ್ಯಮಾಪನವನ್ನು ರಸ್ತೆ ಅಧಿಕಾರಿಗಳು ಮಾಡಬೇಕು.**ಚಾಲನಾ ಪರವಾನಗಿ ಮತ್ತು ವಾಹನ ಪರವಾನಗಿ** ಪ್ರಾಧಿಕಾರಗಳು ಅವುಗಳ ನೋಟ ಮತ್ತು ಚಾಲನಾ ಶೈಲಿಯಂತಹ ಎವಿ ಅಂಶಗಳ ಬಗ್ಗೆ ಮಾರ್ಗಸೂಚಿಗಳನ್ನು ಮಾಡಬೇಕಾಗಿದೆ ಮತ್ತು ನಡವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಯ ಪರಿಣಾಮಗಳನ್ನು ಉತ್ತಮವಾಗಿ ನಿರ್ವಹಿಸಲು ಮಾನವ ಚಾಲಕರಿಗೆ ತರಬೇತಿ ನೀಡಬೇಕಾಗಿದೆ. **ಎವಿ ಕಾರು ತಯಾರಕರು** ಇತರ ರಸ್ತೆ ಸಂಚಾರದ ಮೇಲೆ ತಮ್ಮ ವಾಹನಗಳು ಮತ್ತು ವ್ಯವಸ್ಥೆಗಳ (ನೋಟ ಮತ್ತು ನಡವಳಿಕೆ-ಸಂಬಂಧಿತ) ಪರಿಣಾಮಗಳನ್ನು ತನಿಖೆ ಮಾಡಬೇಕು. ಅಲ್ಲದೆ, ಎವಿ ತಯಾರಕರು ಸುತ್ತಮುತ್ತಲಿನ ದಟ್ಟಣೆಯ ಮೇಲೆ ವಿವಿಧ ವಾಹನ ಒಳಗಿನ ಸ್ಥಾಪನೆಗಳ ಪರಿಣಾಮಗಳ ಬಗ್ಗೆ ಬಳಕೆದಾರರಿಗೆ ಅರಿವು ಮೂಡಿಸಬಹುದು. ಉದಾಹರಣೆಗೆ, "ಕ್ರೂಸ್ ಕಂಟ್ರೋಲ್" ರಕ್ಷಣಾತ್ಮಕ ಸ್ಥಾಪನೆಗಳನ್ನು (ದೊಡ್ಡ ಸಮಯದ ಮುನ್ನಡೆಯಂತಹ) ಇಟ್ಟುಕೊಳ್ಳುವುದರಿಂದ ಇತರ ಚಾಲಕರು ಎವಿಗಳ ಮುಂದೆ ನಿಕಟ ಕುಶಲತೆಯನ್ನು ಮಾಡಬಹುದು ಎಂದು ಎವಿ ಬಳಕೆದಾರರಿಗೆ ತಿಳಿಸಬಹುದು. ಆದರ್ಶವಾಗಿ, ಸುರಕ್ಷಿತ ಮತ್ತು ಆರಾಮದಾಯಕ ಚಾಲನಾ ಪರಿಸ್ಥಿತಿಗಳನ್ನು ಖಚಿತಪಡಿಸಲು ಎಲ್ಲಾ ವರ್ಗಗಳ ನಡುವೆ ಹತ್ತಿರದ ಸಹಕಾರ ಅಗತ್ಯವಿದೆ.

ಪ್ರಾಯೋಗಿಕ ಪರಿಣಾಮಗಳ ಜೊತೆಗೆ, ಈ ಪ್ರಬಂಧವು ಭವಿಷ್ಯದ ಸಂಶೋಧನಾ ನಿರ್ದೇಶನಗಳನ್ನು ಸೂಚಿಸುತ್ತದೆ. ಇತರ ಸಂದರ್ಭಗಳಲ್ಲಿ ವರ್ತನೆಯ ಹೊಂದಾಣಿಕೆಗಳು (ಉದಾಹರಣೆಗೆ, ಮೋಟಾರುಮಾರ್ಗಗಳು, ನಗರ ರಸ್ತೆಗಳು) ಮತ್ತು ಚಾಲನಾ ಕುಶಲತೆಗಳು (ಉದಾಹರಣೆಗೆ, ಚಾಲನಾ ಪಥ ಬದಲಾಯಿಸುವುದು, ತುರ್ತು ತಡೆ) ತನಿಖೆ ಮಾಡಬೇಕಾಗಿದೆ. ದೀರ್ಘಕಾಲೀನ ನಡವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಯ ಮೇಲಿನ ಪರಿಣಾಮಗಳನ್ನು ಅಧ್ಯಯನ ಮಾಡುವುದು ಸಹ ಮುಖ್ಯವಾಗಿದೆ ಏಕೆಂದರೆ ಅಲ್ಪಾವಧಿಯಲ್ಲಿ ಗಮನಿಸಲಾದ ನಡವಳಿಕೆಗಳು ದೀರ್ಘಕಾಲೀನ ನಡವಳಿಕೆಗಳಿಗಿಂತ ಬಹಳ ಭಿನ್ನವಾಗಿರಬಹುದು. ಸಂಶೋಧನೆಯ ಮತ್ತೊಂದು ಆಸಕ್ತಿದಾಯಕ ದಿಕ್ಕು ಎವಿಗಳ ಇಎಚ್ಎಂಐಗಳು (ಬಾಹ್ಯ ಮಾನವ ಯಂತ್ರ ಇಂಟರ್ಫೇಸ್ಗಳು) ಎಚ್ಡಿವಿಗಳೊಂದಿಗಿನ ಪರಸ್ಪರ ಕ್ರಿಯೆಗಳ ಮೇಲೆ ಬೀರುವ ಪರಿಣಾಮವಾಗಿದೆ. ಎವಿಗಳ ವಿಭಿನ್ನ ನುಗ್ಗುವ ದರಗಳನ್ನು ಹೊಂದಿರುವ ಮಿಶ್ರ ಸಂಚಾರದಲ್ಲಿನ ಪರಸ್ಪರ ಕ್ರಿಯೆಗಳು ಮತ್ತು ಪರಿಣಾಮಗಳನ್ನು ತನಿಖೆ ಮಾಡುವುದು ಸಹ ಮುಖ್ಯವಾಗಿದೆ. ಮತ್ತೊಂದು ನಿರ್ಣಾಯಕ ಅಂಶವೆಂದರೆ ಸಂಚಾರ ಸುರಕ್ಷತಾ ಪರಿಣಾಮ, ಇದನ್ನು ಅಧ್ಯಯನ ಮಾಡಬೇಕು. ಅಂತಿಮವಾಗಿ, ಸಂಚಾರ ದಕ್ಷತೆಯ ಮೇಲೆ ಅಳೆಯಲಾದ ಮ್ಯಾಕ್ರೋಸ್ಕೋಪಿಕ್ ಪರಿಣಾಮಗಳ ಮೇಲೆ ನಡವಳಿಕೆಯ ಹೊಂದಾಣಿಕೆಯನ್ನು ಪರಿಗಣಿಸುವ ಪರಿಣಾಮವನ್ನು ಮತ್ತಷ್ಟು ತನಿಖೆ ಮಾಡಬೇಕು. ಈ ಪ್ರಬಂಧವನ್ನು ಹೊರತುಪಡಿಸಿ, ಈ ವಿಷಯವನ್ನು ಇನ್ನು ಎಲ್ಲಿಯೂ ಅಧ್ಯಯನ ಮಾಡಲಾಗಿಲ್ಲ.

Reader's Guide

Dear reader, this is a guide that helps navigating this dissertation. You can find the chapter titles suggesting their focus and the method used. There is also a description that takes you a step deeper in what the chapters offer. Additionally, there is a preview that gives you a taste of the findings.

To gain insights of human drivers behavior in mixed traffic, we conducted a first exploration of human drivers' behavioral adaptation in mixed traffic. We set up a **field test** where human drivers interacted with an automated vehicle in a **Wizard-of-Oz** experiment during **gap acceptance**, **car following**, and **overtaking**.

Preview*: human drivers perform closer manoeuvres in front of automated vehicles*

To gain insights into human drivers' **car following behavior**, a **driving simulator experiment** was set up where drivers followed a lead vehicle appearing either as an automated vehicle or human-driven vehicle. We estimated the **Intelligent Driver Model** (IDM) and the IDM+ to get insights into **driving behavior parameters**.

Preview*: human drivers have smaller desired speeds when following a vehicle that drives like an AV and is recognizable as an AV*

To gain insights into human drivers' **gap-acceptance behavior**, we set up a **driving simulator experiment**, drivers were asked to enter a major road while approaching from a minor road at a **T-intersection**, which involved waiting for an acceptable gap on the major road traffic. We performed **descriptive analyses** to check the effects of **AV recognizability and AV driving style** on human drivers' gap acceptance behavior.

Preview*: human drivers accept larger gaps when automated vehicles are recognizable and perceived as less defensive*

To understand the impact of behavioral adaptation on traffic efficiency, we **modelled** human drivers' **gap acceptance behavior** and implemented that in a **traffic microsimulation** network. We studied the impact of automated vehicles' **recognizability, their driving style, and their penetration rate** on the **traffic efficiency** of an unsignalized T-intersection.

Preview*: not considering behavioral adaptation can result in an underestimation of delay*

Chapter 1
Introduction

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1. Introduction

1.1. Background: The emergence of automated vehicles

Humans have found different ways to satisfy the need to move from one place to another. Early humans walked many kilometers every day in search of food and shelter or just for plain curiosity. Slowly, humans began to explore other transport modes that we found in nature such as horses, donkeys, and camels. Around 3500 BC, a significant revolution occurred, that is, the invention of the wheel. Since then, we have progressed through many revolutions in how we achieve transportation of people and goods. Fast-forwarding towards the end of the 19th century and early 20th century, we witnessed the boom of personal vehicles. Today, vehicles are ubiquitous and are known all around the world, transcending age, gender, and socioeconomic disparities. In fact, it was found that "auto", which is the Dutch word for a car, is among the first 5 words learned by a baby (Opgroeien).

As vehicles started dominating our transportation network, along with their numerous benefits, concerns began to rise. Increasing rates of crashes, congestion, pollution, and the space they occupy in our (urban) living environment stirred the need for effective solutions to these transportation problems. Some solutions include demand management (managing the need to travel), supply management (for example, building new roads and optimizing traffic light intersections), road infrastructural changes, promoting safe and socially compliant driving behavior, electrification, and improving public transportation and active modes such as biking and walking.

One of the solutions that has been regarded as having potential to solve the above-mentioned transportation problems is the technology of automated vehicles. Automated vehicles (AVs) are vehicles that can perform (part of) the driving tasks themselves without requiring full human control. By automating the driving task, it is expected that the mistakes and errors that human drivers make (e.g., distraction, fatigue, misjudgment), which contribute to more than 90% of crashes, can be corrected. For example, AVs equipped with lane keeping systems are designed to keep the vehicle within the lane, preventing unintended deviation due to driver distraction or error. AVs with emergency braking assist technology are designed to detect an imminent danger and automatically apply the brakes in case of critical situations such as sudden braking of a lead vehicle or a pedestrian crossing unexpectedly in front of the vehicle. Attempts are also being made to explicitly program AVs to drive not just safely, but also in a way to achieve additional goals. For example, AVs can drive in an environmentally conscious way (for example by avoiding sharp accelerations or decelerations) or prioritize the performance of the entire road network system as opposed to only their individual benefit (for example by coordinating their time of arrival at intersections such that the delay for all vehicles is minimum) (Elliott et al., 2019). AVs can also support people with disabilities and/or impairments that prevent them from driving to gain access to desired destinations in society. Moreover, automation of vehicles enables vehicle sharing, thereby reducing the spatial footprint of cars, especially with respect to parking. Overall, AVs are expected to enhance road safety, improve traffic efficiency, reduce emissions, and promote livability and accessibility (Greenblatt & Shaheen, 2015; Piao et al., 2016).

Inspired by the transformations that AVs promise to bring, AVs were and are being deployed across the world. Several car manufacturers are actively working towards developing fully automated vehicles. In San Francisco, more than 500 self-driving cars (fully automated) are operating on public roads (Paul, 2024). In the European Union, all new vehicles sold from 2022 must mandatorily have a certain range of advanced driver assistant systems (European Commission, 2018). For cars for example, this includes lane-keeping systems, intelligent speed assistance systems, and automated braking systems. Overall, we are witnessing an increasing number of AVs, fully automated or partially automated, deployed on our public roads.

While these developments related to AVs are well-intentioned and even (partially) underpinned by empirical evidence, there are concerns emerging about the actual impact that AVs are making and can make. There are several reasons for this. First, the crash rates of AVs are measured to be higher than those of HDVs (US Department of Transportation, 2023). While this increase in AV-related crashes can be correlated with increasing AV deployment, and that AV-related crashes grab larger attention in the media, it is nevertheless a valid concern that AVs are being involved in crashes on public roads. AVs also have limitations to how well they execute their driving tasks. For instance, lane-keeping systems can perform poorly in rainy conditions, or in the presence of poor-quality lane markings, and have trouble navigating sharper curves, and can even mistakenly detect other elements on the road as lane markings and lead to deviating from the current lane (Utriainen et al. (2020); Reddy et al. (2020)). Additionally, drivers using adaptive cruise control (ACC) systems in traffic jams often experience that the vehicle maintains a very large distance from the lead vehicle, which allows vehicles from the other lanes to cut in easily in front of them (Marsden et al., 2001). Therefore, despite the expected transformational benefits of AVs, they are under scrutiny regarding their exact impact, particularly when they will be sharing the road with other road users.

1.2. The question of AVs' impact on human drivers

An important reason for the concern about AVs' deployment is that they (will) share the road space with other road users. While there is already great attention towards improving the driving ability of AVs, this is largely focused on the AV itself. For example, there is a vast amount of literature on how to improve the detection performance of AVs (Van Wyk et al., 2020), what kind of communication systems they must have (Sarker et al., 2020), the mechanisms of how they would keep their trajectory in a lane (Hu et al., 2019), how they should drive in different situations (Schieben et al., 2019), and how they manage the transition of driving control to the human driver if present (Lu & de Winter, 2015). In addition to these challenges, it is important to consider that AVs will be driving in traffic consisting also of human-driven vehicles (henceforth we will refer to traffic consisting both of AVs and human-driven vehicles (HDVs) as 'mixed traffic', and to traffic consisting only of HDVs as 'conventional traffic'). Therefore, it is essential to also look at what impacts AVs (would) have on HDVs. There have been few studies that have investigated the impact that AVs could have on HDVs. These can be classified into two groups: the first group includes studies looking at micro/meso-level impacts, that is, how HDVs change their driving behavior because of interactions with AVs, while the second group includes studies predicting the macro-level impacts of AVs on traffic efficiency, traffic safety, and emissions.

The first group of studies is still relatively new but nevertheless offers important early evidence on how AVs can change HDVs' driving behavior. For example, HDVs were found to reduce the gap they maintain with their lead vehicles when there were AVs driving in the adjacent lanes maintaining smaller gaps with their leaders (Gouy et al., 2014). Trust in AVs was also found to be an influencing factor where "AV-believers" maintained smaller time headways when following an AV as compared to "AV skeptics" (Zhao et al., 2020). Changes in HDVs' driving behavior have also been observed in lane changing and gap acceptance behavior. Drivers exhibited greater steering magnitude and steering velocity when lane changing in an AV platoon environment, which further increased with increasing AV penetration rate (the share of vehicles on the road network that are AVs) (Lee et al., 2018). Another study observed drivers to accept gaps more often in front of AVs than HDVs (Trende et al., 2019). These changes in the behavior of HDVs in mixed traffic compared to conventional traffic can be referred to as "behavioral adaptation" (Kulmala & Rama, 2013). In the ensuing chapters 2, 3, 4, and 5 of this dissertation, such studies are listed and discussed more extensively, specifically when discussing current literature (Introduction or Background sections). Overall, earlier studies have found evidence that HDVs change their driving behavior during interactions with or because of interacting with AVs. However, this evidence is still in an early stage and there is a lack of clarity, and further insights need to be gained into how exactly AVs – because of their appearance, driving style, penetration rate, and also due to drivers' trust in them – affect HDVs' driving behavior. These factors that are specific to mixed traffic such as AV appearance, AV driving style, AV penetration rate, and trust in AVs can be called as mixed traffic factors.

The second group of studies predict performance indicators such as traffic safety and efficiency in different scenarios involving AVs. These performance indicators are generally evaluated using simulation studies (including micro-, meso- and macrosimulations), expert opinions, meta-analysis (literature study) (Vahidi & Eskandarian, 2003), controlled experiments, and naturalistic studies. Microsimulation is a very popular tool to get concrete insights into specific indicators of traffic performance. For example, an increasing penetration rate of AVs was found to increase traffic efficiency (because of reduction in traffic conflicts) (Papadoulis et al., 2019). On the other hand, some studies showed that AVs without connectivity (adaptive cruise control for example) can decrease traffic efficiency by having larger average spacing and headways (Schakel et al., 2017). Also, the introduction of AVs in mixed traffic was found to boost traffic safety (measured by number of longitudinal conflicts and driving volatility) (Arvin et al., 2020). Such studies are also discussed in greater detail in the later chapters of this dissertation, particularly chapter 5.

The prediction of traffic safety and efficiency of mixed traffic conditions is important because these constitute the input for relevant decision makers (for example, road authorities, policymakers, vehicle licensing authorities, car manufacturers) who steer the deployment of AVs on public roads. In these previous studies to predict the impacts of AV deployment on mixed traffic performance, assumptions were made on the driving behavior of AVs as well as

HDVs. Generally, HDVs are defined according to how they currently behave. However, this assumes that HDVs drive in the same way in mixed traffic in the presence of AVs as they do in current conventional traffic conditions. However, as previously discussed, there is increasing evidence that HDVs change their driving behavior in mixed traffic. This prompt attention to how we understand and define HDV driving behavior in mixed traffic conditions. Understanding the behavior of HDVs in mixed traffic is crucial as it directly has an impact on the validity of the AV-impact studies, and consequently can help decision makers make better informed decisions. In essence, we need a better understanding of HDVs' driving behavior in mixed traffic conditions, particularly the impact of AVs on HDVs' behavior. This would be useful to make more accurate predictions or impact assessment studies looking at the deployment of AVs in mixed traffic, therefore assisting in making decision-makers better informed in making traffic safe and efficient.

1.3. Scientific gaps

From the synthesis of current literature, the following scientific gaps were identified:

1. The evidence that HDVs change their behavior when interacting with AVs is still at a nascent stage. Studies investigating this behavioral adaptation are gradually increasing, but this topic remains largely unexplored. For example, it is not yet clear what are the specific factors – relevant to mixed traffic conditions – that affect HDV driving behavior in mixed traffic, and what is the precise nature of their effect. There is a need for more in-depth investigation and more evidence into the effects of AVs on the driving behavior of HDVs. For example, clear answers to questions such as how do the driving styles of AVs affect HDV behavior, how does this effect change when combined with the recognizability of the AV, and what role does driver characteristics play in this process, are still missing.
2. Existing studies almost all focus on the aspect of car-following behavior on straight road sections. In addition to car-following, there is also a need to research the impacts of AVs on other driving maneuvers of HDVs' driving behavior (e.g., gap-acceptance, lane-changes) and in different road situations (e.g., road sections, intersections).
3. Driving behavior models for HDVs, such as for car following and lane changing, were mostly calibrated for conventional traffic conditions. HDV driving behavior models specifically designed and calibrated for mixed traffic conditions, considering mixed traffic specific factors such as AV recognizability and AV driving style, do not yet exist.
4. Existing simulation studies aiming to predict the impacts of AVs on traffic safety and efficiency use HDV driving models that are valid in conventional traffic. There is a need to conduct simulation studies that consider HDV driving behavior models that are designed and developed for mixed traffic conditions.
5. Even though current simulation studies assume that HDVs drive in the same way in mixed traffic as in conventional traffic, there was no study so far that tested this assumption. We do not know if incorporating behavioral adaptation in simulation studies results in any (meaningful) change in the results of the study. This is important to investigate and remains to be determined.

1.4. Scope

This dissertation focuses on the HDV behavior, specifically cars. More specifically, how AVs would affect HDVs' driving behavior. Hence, the behavior of other road users, such as bikes and pedestrians, was out of the scope of this thesis. As for the road scenarios, this dissertation focuses on motorways, provincial roads, and unsignalized intersections, where drivers perform routine driving tasks such as car-following, lane changing, and gap acceptance. Safety-critical situations such as emergencies were out of the scope. The research conducted in this dissertation is applicable to all levels of automation. The specific descriptions of AV configuration are detailed in the relevant chapters. This dissertation focuses exclusively on the impacts of AVs on traffic efficiency, which relates to (among other things) the travel time and the delay experienced by drivers. Traffic safety was out of the scope of this dissertation due to simulation tools limitations.

1.5. Research Questions and research approach

The main question that this research addresses is:

What are the impacts of automated vehicles on the driving behavior of human-driven vehicles, and its consequences on mixed traffic efficiency?

To address the main research question, sub-research questions were formulated as follows:

1. What are the potential behavioral adaptations of human drivers during their interactions with AVs?
2. What is the impact of AVs on the car following behavior of HDVs?
3. How do human drivers perform gap acceptance maneuvers in mixed (automated and human-driven) traffic at priority T-intersections?
4. How does mixed traffic affect the traffic efficiency of priority T-intersections?

Understanding the driving behavior of HDVs in mixed traffic enables more accurate insights and more valid predictions of the impacts of AVs on traffic efficiency in mixed traffic. To achieve this, the interactions between HDVs and AVs must be investigated by examining different aspects of HDV driving behavior such as car-following, lane-changing, gap acceptance, in the presence of and while interacting with AVs in mixed traffic. When such an understanding is obtained, we could develop mathematical models that capture these interactions. These mathematical models could then be implemented in traffic simulations, so we can gain insights into the impacts on traffic efficiency of AVs in mixed traffic.

This dissertation uses a combination of methods including literature review, stakeholders' input, experiment design methods, data collection using driving simulators and field test experiments, and simulation tools to address the research questions. This dissertation used an evidence-based approach to answer these research questions. Empirical data collection methods included driving simulators and controlled field test experiments which provided a strong underpinning for the analyses. Such controlled data collection methods were suitable because firstly they provided a high degree of control over the experiment conditions to test specific effects, and secondly, they were practically and ethically better suited due to the safety of people involved, compared to naturalistic studies or testing with AVs on public roads. Furthermore, microsimulation tools were also employed to address the final sub-research question. The chapters in this dissertation elaborate on the specific methodologies adopted for the corresponding research questions.

This dissertation was part of a larger project that had a user committee comprising of partner organizations including road authorities, research organizations, consultancy companies, road infrastructure equipment manufacturer, and a car manufacturer. A close collaboration with these partners contributed to making the scope of this dissertation relevant to practice. It also provided practical insights and opportunities and resources to strengthen the research methodology.

1.6. Scientific contributions

The work conducted in this dissertation could provide insight and inspiration for researchers and research organizations to not only use the methods, results, and insights in their own research but also to direct their research efforts in the subject of behavioral adaptation in mixed traffic, or in the impact assessment of AVs. This dissertation makes the following contributions to science:

1. The research conducted in this dissertation provides new evidence of HDV behavior and the resulting behavioral adaptations in mixed traffic conditions. Existing evidence is still at a nascent stage thereby making such new insights in this topic valuable for better understanding of mixed traffic conditions.
2. This dissertation investigates multiple human driving behavioral maneuvers in mixed traffic, namely car following behavior behind an AV compared to HDV, overtaking an AV compared to HDV, gap acceptance from standstill in front of AV compared to AV. Behavioral adaptations in all these driving maneuvers were studied.
3. It provides empirical insights that have not been done before in this field, through the combination of field tests and driving simulator experiments that allowed drivers to perform different types of driving tasks such as car-following, overtaking, and gap acceptance. Findings from the different data collection methodologies allows for a clearer understanding of HDV behavior in mixed traffic.
4. This dissertation investigates the implication of considering HDV behavioral adaptation in simulation studies of mixed traffic. To the best of our knowledge, this is the first study that implements the observed behavioral adaptation in traffic simulation to study the impact on traffic efficiency. Specifically, the traffic impacts were analyzed by comparing scenarios with and without behavioral adaptation considered. This comparison highlighted the significance of incorporating HDV behavioral adaptation, as it revealed the extent to which traffic impacts might be overestimated or underestimated if behavioral adaptation was ignored.
5. This dissertation develops HDV behavioral models specific to mixed traffic conditions. In particular, models for car following and for gap acceptance at unsignalized intersections were estimated considering mixed traffic factors such as AV appearance, AV driving style, and trust in technology. These models can be used to inspire future research efforts by exploring methods and possibilities of capturing these interactions through modelling. Additionally, they can be implemented directly for mixed traffic studies.
6. By focusing on the factors affecting HDV behavior, this dissertation provides insights into what aspects of AVs' characteristics affect HDV behavior and how do they affect it. Particularly, how the recognizability of AVs and their driving styles affect HDV behavior.

1.7. Contributions to practice

This study makes the following contributions to practice:

1. Road authorities could use the results of this dissertation in their decisions related to the management of road infrastructure. This dissertation's insights into how HDVs drive in mixed traffic can have implications on road infrastructure. For instance, driving behavioral changes of HDVs can have a direct impact on traffic flow and therefore on capacity. Therefore, road authorities must take into consideration possible HDV behavioral adaptations in their decision-making processes.

2. Vehicle licensing authorities can understand the impact that AVs can have on HDVs. Specific aspects of AVs such as their appearance (recognizability) and their driving style can impact HDV driving behavior. Vehicle licensing authorities can consider implementing such insights in the vehicle standards and licensing or approval processes such that vehicle manufacturers can design AVs that are conducive to society's traffic vision.
3. Vehicle manufacturers could use the results of this dissertation to understand the impact that AVs can have on HDVs. This can help them to (re)consider critical decisions related to the design of AVs such as their appearance and their driving style. Such decisions can therefore be made with greater awareness of the implications it can have not only for the AV users but also HDVs present in the surrounding traffic, whose behavior ultimately also affects AV users. In this way, they can take a greater responsibility in creating more desirable traffic conditions in mixed traffic.
4. Driving license authorities and driving instructors can also find the results of this dissertation useful in the training and licensing of drivers. The understanding of AVs' characteristics, behavior, strengths and limitations, and the concept of behavioral adaptation of HDVs in mixed traffic could be useful in the design and development of driver training and education processes. In this way, driving license authorities and driving instructors can help human drivers in being better prepared for driving in mixed traffic conditions.

1.8. Conceptual framework of this dissertation

This dissertation focused on investigating the behavior of HDVs in mixed traffic and the resulting impacts on traffic efficiency. This can be seen as a process composed of three components: the factors affecting driving behavior, the driving behavior itself, and the impacts of driving behavior. Figure 1.1 depicts a conceptual framework for this research, which also serves as an outline for this dissertation. The HDV is positioned in the center, being the subject of this research. The HDV is affected by three groups of factors: the road environment, traffic conditions, and the characteristics of the human driver. These are depicted in the three circles that have arrows pointing to the HDV. The road environment consists of elements such as weather conditions (e.g., sunny, rainy, fog) and road infrastructure/situations (e.g., highway section, urban intersections, roundabouts). Traffic factors include the characteristics and behavior of other road users such as pedestrians, bikes, other cars, buses, and – in mixed traffic – AVs. Driver factors relate to the personal characteristics of the driver of the HDV (e.g., age, gender, driving style, mental workload, and situational awareness).

All these three groups of factors together affect the HDV's driving behavior. In Figure 1.1, the HDV's behavior includes the following components: car-following, lane changing, overtaking, gap acceptance, and emergency braking. Car-following behavior relates to how the HDV follows its leader (i.e., the vehicle in front of it), and characterizes it in terms of variables such as time gap (the time difference between the rear of the leader and the front of the follower vehicle), acceleration behavior, and space gap (the distance between the rear of the leader and the front of the follower). Lane changing behavior refers to how the vehicle performs a change in the lane on the road. This comprises of the trigger for desiring the lane change (e.g., to maintain a desired speed or exit a motorway), an acceptable gap in the target lane, and the execution of the lane change itself in terms of aggressiveness for example. Overtaking behavior describes how a vehicle overtakes another vehicle driving in the same direction (either on the same lane or on a parallel lane). The overtaking behavior comprises of the trigger for desiring to overtake, the gap from the leader when starting to overtake, the lateral gap while overtaking, and the remaining gap from the following vehicle when returning to the lane after overtaking.

Gap acceptance, in this dissertation, describes the behavior of a vehicle that is approaching from a minor road and intending to enter a major road, searching for an acceptable gap in the major road traffic stream. Emergency braking refers to when the vehicle brakes at a high rate as a response to a critical situation endangering safety.

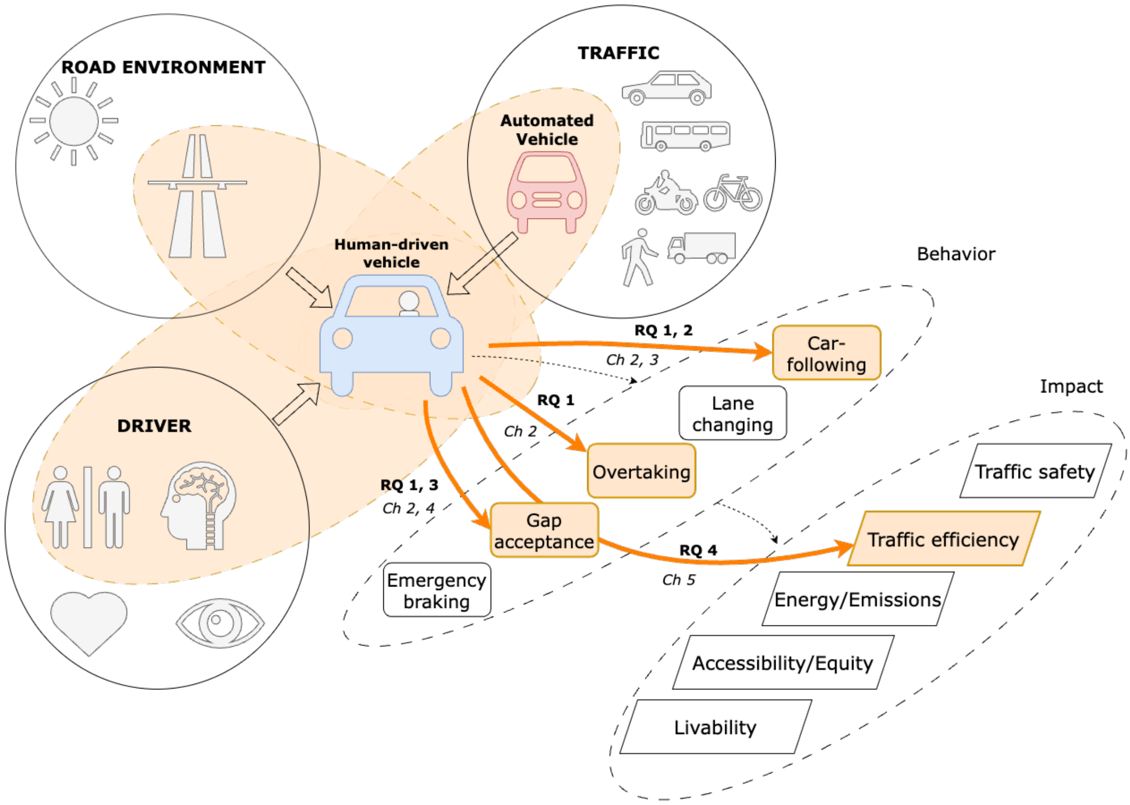

Figure 1.1: Conceptual framework as an outline for this dissertation

These driving maneuvers define the core behavior of the HDV in traffic. These driving behaviors of the HDV and of other vehicles (including AVs) in traffic has an impact on the state of the traffic at a macroscopic level. Vehicles driving very close to each other at high speeds may have a positive effect on traffic efficiency but a negative effect on traffic safety due to high risk of a crash. Vehicle behavior can have an impact on traffic safety, traffic efficiency, energy/emissions, accessibility/equity, and livability.

An orange color shade highlights the scope of this dissertation in Figure 1.1. This scope considers the road situations in the “road environment” factor, AVs in the “traffic” factor, and personal characteristics of the driver as the “driver” factor. As for the type of behavior, this dissertation focused on car-following, overtaking, and gap acceptance. Finally, this dissertation studied the impact of gap acceptance on traffic efficiency. The research questions (RQs) are also depicted as thick arrows in Figure 1.1.

1.9. Outline of dissertation – Chapter division

This dissertation is organized in line with the RQs presented previously, which are connected to the chapters as follows:

Chapter 2: Investigating behavioral adaptation: A field test experiment [RQ1]

Chapter 3: Investigating car-following behavior: A driving simulator experiment[RQ2]

Chapter 4: Investigating gap-acceptance behavior: A driving simulator experiment [RQ3]

Chapter 5: Investigating the impact of behavioral adaptation on traffic efficiency: A microsimulation approach [RQ4]

Chapter 6: Discussion and Conclusions

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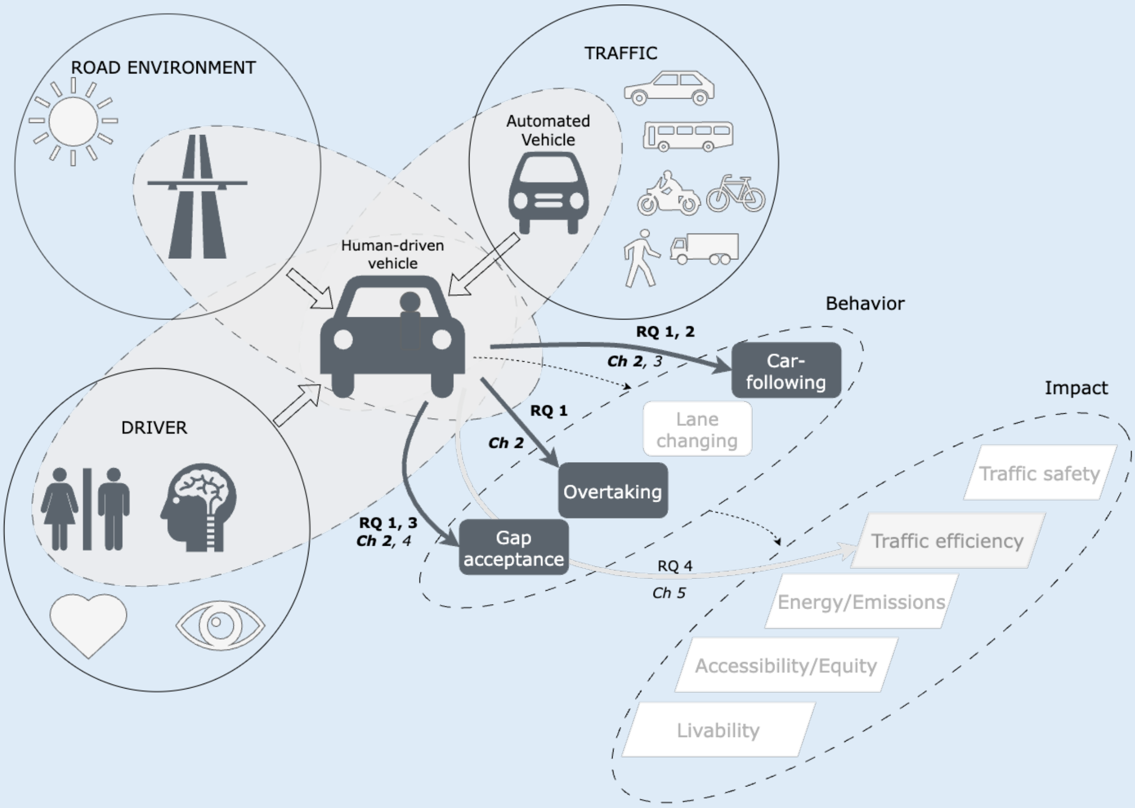
Chapter 2

Investigating Behavioral Adaptation: A Controlled Field Test Experiment

In this chapter, we conduct a first exploration of human drivers' behavioral adaptation in mixed traffic. We set up a controlled field test where human drivers interact with an automated vehicle in a Wizard-of-Oz experiment during gap acceptance, car following, and overtaking maneuvers. Is there an effect of recognizability of AVs on human drivers' behavior?



Highlights

- Human drivers' interactions with automated vehicles were studied in a controlled field test.
- Human drivers adapt their driving behavior when interacting with automated vehicles.
- Drivers interacting with recognizable automated vehicles adopt smaller critical gaps.
- After overtaking, drivers merge closer in front of recognizable automated vehicles.
- There could be potential exploitation of automated vehicles by drivers in traffic.

This chapter is based on the publication: Soni, S., Reddy, N., Tsapi, A., van Arem, B., & Farah, H. (2022). *Behavioral adaptations of human drivers interacting with automated vehicles.* Transportation Research Part F: Traffic Psychology and Behaviour, 86(February), 48–64. https://doi.org/10.1016/j.trf.2022.02.002

Chapter 2
Table of Contents

2. Investigating Behavioral Adaptation: A Controlled Field Test Experiment

2.1. Introduction

The topic of automated driving is currently in the limelight of researchers, policymakers, and vehicle manufacturers due to its potential benefits to road transportation, especially in terms of traffic flow and safety (Aria, Olstam, & Schwietering, 2016). These benefits result from the technological capabilities of AVs, such as the ability of platoon formation, shorter reaction times, shorter following headways, ability to continuously detect their surroundings, keeping track of all nearby road users, and smooth, stable, and predictable driving (Winkle, 2016). However, in the early phases of automation, mixed traffic will occur where both AVs and Human Driven Vehicles (HDVs) will coexist and interact.

Various studies that predicted the benefits of AVs implicitly assumed that human drivers would not change their driving behavior while interacting with AVs (Friedrich, 2016; Winkle, 2016). However, the recognizability of AVs due to their appearance might play a role in the behavioral adaptation of interacting human drivers (Fuest, Feierle, Schmidt, & Bengler, 2020). Since human drivers may have mixed opinions and trust towards AVs, they might behave differently when interacting with an AV compared to when interacting with an HDV. The phenomenon of behavioral adaptation is defined as "unintended change in the behavior of the users with the introduction of a new system against the system's intended designed operation" (OECD, 1990). Behavioral adaptation generally focuses on the negative effects of the phenomenon as it may jeopardize the intended benefits of the system (Saad, 2004). Behavioral adaptation can appear in many different forms when driving, such as speed management (Melman, Abbink, Van Paassen, Boer, & De Winter, 2018), following distance, the way of overtaking or lane changing, braking, level of attention, and gap acceptance (Draskóczy, 1994).

A large number of studies have investigated how users of AVs take over control (Gold, Damböck, Lorenz, & Bengler, 2013; Varotto, Farah, Bogenberger, van Arem, & Hoogendoorn, 2020; Winter, Stanton, Price, & Mistry, 2016) and how vulnerable road users respond to AVs (Fuest, Michalowski, Schmidt, & Bengler, 2019; Palmeiro et al., 2018; Velasco, de Vries, Farah, van Arem, & Hagenzieker, 2021; Velasco, Farah, van Arem, & Hagenzieker, 2019). However, the behavioral adaptation of human drivers interacting with AVs is crucial to traffic safety and efficiency and has not been studied extensively yet. Some field tests and driving simulator studies have provided some evidence of behavioral adaptation of human drivers during their interaction with AVs (Gouy, Wiedemann, Stevens, Brunett, & Reed, 2014; Rahmati, Khajeh Hosseini, Talebpour, Swain, & Nelson, 2019; Trende, Unni, Weber, Rieger, & Luedtke, 2019; Zhao et al., 2020). These studies are summarized in Table 2.1.

Car-following behavior has been studied more extensively than other types of driving behaviors. Few controlled field tests have been conducted to study one-on-one interactions between HDVs and AVs during car-following (Rahmati et al., 2019; Zhao et al., 2020). These studies found a reduction in headways while interacting with AVs, especially for drivers with higher trust in AVs. Similar findings were also observed in several driving simulator studies, where shorter headways were observed while driving near a platoon of automated vehicles (Gouy, 2013; Gouy et al., 2014; Schoenmakers, Yang, & Farah, 2021).

A few studies focused on the gap acceptance behavior of human drivers interacting with AVs. A driving simulator study by Trende et al. (2019) found an increase in gap acceptance frequency while interacting with AVs at an intersection. This suggests drivers' intentions to exploit the technological advantages of AVs and the AVs' ability to perform safer maneuvers. Rad et al. (2021) studied human drivers' behavior on motorways in three different scenarios in a driving simulator. In the first scenario the human drivers interacted with platoons of 2-3 connected and automated vehicles that are mixed in traffic consisting as well of manually driven vehicles (called 'Mixed' scenario). In the second scenario the platoons of connected and automated vehicles drove only on a dedicated lane, which was chosen to be the left most lane on a motorway consisting of 3 lanes (called Dedicated Lane scenario), while the third scenario consisted only of manually driven vehicles (called 'Base' scenario). It was found that human drivers accepted smaller gaps during lane changing maneuvers in the dedicated lane compared to the Mixed and Base scenarios, with up to 12.7% shorter gaps at on-ramps.

In terms of lane-changing behavior, an increase in lane-change duration was observed when HDVs interacted with platoons of AVs (Lee & Oh, 2017; Lee et al., 2018). It was found that the participants experienced a higher psychological burden while driving near platoons of automated vehicles, leading to an increase in lane change duration (Lee & Oh, 2017).

The above studies point to the behavioral adaptation of human drivers when they interact with AVs. However, these studies assume that AVs drive differently than HDVs. Also, most of these studies focused on AV platoons, while only a few on one-to-one HDV-AV interaction. Therefore, there is a need to study these behavioral adaptations further when AV behaves similarly to HDV and when drivers are provided with information regarding the AV.

Trust in AVs plays a major role in shaping the expectations of human drivers towards the driving behavior of AVs. However, trust is highly influenced by the knowledge and information about AVs. Feldhütter, Gold, Hüger, and Bengler (2016) showed that trust in AVs was affected by media and personal experience. From their study, a significant change in trust was found when the participants received basic information about AVs, read media articles, and when they have personally experienced AVs in a driving simulator. Ward, Raue, Lee, D'Ambrosio, and Coughlin (2017) found that trust and acceptability of AV technology varied greatly with the age of people and their knowledge about AVs. When participants were provided with positive knowledge and insights about AV technology, their perceived benefits of AV technology increased, and their perceived risks decreased, leading to an overall improvement in their trust in AV technology. A similar relation between trust and knowledge was also found by Nuñez Velasco et al. (2019).

Table 2.1: Studies focusing on understanding the interactions between HDVs and AVs

Study	Driving behavior	Sample size	Country	Main Findings for Human drivers
Controlled field tests				
Mahdina et al. (2021)	Car-following	9	United States	HDV drivers exhibit lower driving volatility in terms of speed and acceleration. HDV drivers maintain slightly smaller headways with AVs.
Zhao et al. (2020)	Car-following	10	China	AV believers – Small headways maintained with AVs AV sceptics – Large headways maintained with AVs AV neutral – No difference in driving behavior between AVs and HDVs
Rahmati et al. (2019)	Car-following	9	United States	Small headways and smoother driving while following AV in comparison to HDV
Driving simulator studies				
Rad et al. (2021)	Car-following and gap acceptance	51	The Nether-lands	HDV drivers kept smaller headways during car-following and accepted shorter gaps during lane changing in a dedicated lane scenario compared to mixed and base (0% AVs) scenarios.
Schoenmakers et al. (2021)	Car-following	34	The Nether-lands	Shorter time headways near AV platoon when driving in the proximity of a continuous-access and limited-access dedicated lane compared to limited-access dedicated lane with a guardrail
Trende et al. (2019)	Gap acceptance	17	Germany	More frequent gaps are accepted at an intersection with AVs
Lee, Oh, and Hong (2018)	Lane change	30	Republic of Korea	Increase in lane change duration with an increase in AV penetration rate
Lee and Oh (2017)	Lane change	30	Republic of Korea	Increase in lane change duration near AV platoon due to psychological burden
Gouy (2013); (Gouy et al., 2014)	Car-following	42	United King-dom	Decrease in time headways near AV platoon

Hagenzieker et al. (2020) studied the impact of positive and neutral information on cyclists' trust and perception towards interaction with AVs. It was found that positive information regarding AVs increased the trust of cyclists regarding interacting with AVs. In another study by Vlakveld et al. (2020), the bicyclists yielded to the AV more often when they were provided with negative information regarding AVs. This suggests that providing information about AVs affects the interacting actor's perception of AVs.

Several studies found an influence of recognizability of AVs on the behavioral adaptation of road users. Many of these focused, however, on the interactions between AVs and Vulnerable Road Users (VRUs) with no consensus regarding the impact of recognizability (Dey, Martens, Eggen, & Terken, 2019; Nuñez Velasco et al., 2019; Hagenzieker et al., 2020). In a simulation study by Fuest et al. (2020), no subjective or objective differences in driving behavior were observed, when AV was made explicitly recognizable. Given the lack of research, the effect of recognizability still needs to be investigated further.

Most of these studies used driving simulators, while only a few studies have collected empirical data from real-world driving (Rahmati et al., 2019; Zhao et al., 2020). Thus, more empirical research needs to be conducted to fill the research gaps regarding understanding the interactions between HDVs and AVs and in different maneuvers, such as car-following, lane-changing, and gap-acceptance. Therefore, this research investigates the potential behavioral adaptation of human drivers when interacting with recognizable AVs, with the help of a controlled field test.

The rest of the paper is structured as follows. Section 2.2 presents the research main objective and the underlying research question. Section 2.3 discusses the research methodology, experimental design, and data collection process. Insights into the data processing and analysis method are provided in Section 2.4. Section 2.5 presents the results of behavioral adaptation observed in different types of driving behaviors. Finally, section 2.6 concludes this paper with a discussion and recommendations.

2.2. Research Objective and Research Question

The main objective of this study is to investigate one-on-one interactions between AVs and HDVs during early phases of automation when the penetration level of AVs in road traffic is not high enough to harvest the benefits of platooning. Therefore, the resulting research question is:

What are the potential behavioral adaptations of human drivers during their interactions with an automated vehicle?

This research focuses on three driving behaviors:

- Gap acceptance at un-signalized intersections (critical gaps)
- Car-following behavior (longitudinal control)
- Overtaking behavior (longitudinal and lateral control)

In addition, this research studies the effect of positive/negative information about AVs on the driving behavior of human drivers and the change in their trust in the AV over multiple interactions.

2.3. Methods

A controlled field test was conducted in which HDV drivers interacted with both HDVs and AVs. The HDV drivers are referred to in this study as ‘Participants’. The participants were asked to drive in their own vehicle (because of COVID-19 restrictions). During the field test, the participants interacted with an instrumented test vehicle that could be set up to appear as an AV. The instrumented test vehicle, referred to in this study as the ‘Test Vehicle’ (TV), collected data on the driving behavior of the participant during their interactions. The field test was approved by the Human Research Ethics Committee (HREC) of the Delft University of Technology, the Netherlands.

2.3.1. Field test location

The field test was conducted on a 3 km long straight road section in Noordzeeweg near the town of Rozenburg in the Netherlands. The selected location provided two parking lots on both sides of the road section, which were used as start/end locations of the participant and the TV. Also, a tower was present in the middle of the road section, which was used as a reference point. The test route had one 3.5-m wide lane per direction separated by dashed lane markings (i.e., overtaking was allowed). The traffic intensity of the test location was very low (around 30 vehicles per hour), and the speed limit of the road section was 60 km/h.

2.3.2. Field test setup

The experiment was designed in such a way that the participant drove between points A and B in his/her own vehicle, and the TV was driven between points 1 and 2 (see Figure 2.1). In a single run of the field test, the participant either drove from point A to point B or vice versa, whereas the TV was driven from point 1 to point 2 or vice versa, respectively. A single run, therefore, was defined as driving the road stretch in one direction. The TV always started from the parking lot near the start location of the participant. In each run of the field test, the participant interacted with the TV and the interactions included: gap acceptance, car-following and overtaking. The participants were instructed to reach their end location as described in Figure 2.1.

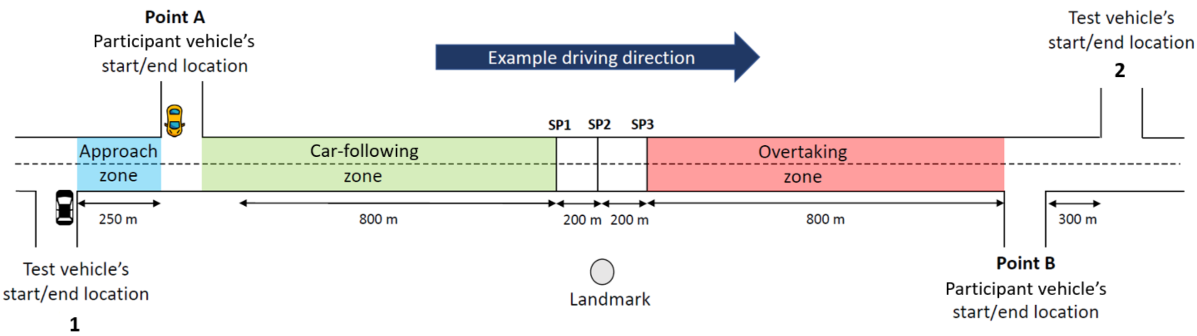


Figure 2.1: The experiment field test plan (SP1, SP2 & SP3 indicate slow-down points).

At the start of each run, the participant and TV positioned themselves in their respective starting locations. The participants were instructed to start from point A and reach point B while the TV drove from point 1 to point 2. The interactions between the participant and the TV took place in the following manner:

1. Gap acceptance: A run began when the TV started driving from its start location point 1 and approached the participant (point A) at a constant speed of 40 km/h. This speed provided ample opportunity for the participant to observe the type of vehicle (as anecdotally confirmed for all participants). From the participant's perspective, the TV approached from its right-hand side in the opposite (further away) lane. When the TV was approaching the participant in the approach zone (blue zone in Figure 2.2), the participant was expected to indicate the last moment when she/he would decide to merge in front of the approaching TV, i.e., their critical gap. The participant indicated the critical gap by means of a hand gesture (putting the hand down when it was not safe to cross anymore (Figure 2.2, top)). However, the participant was not expected to take any action at this point for safety reasons.
2. Car-following: Once the TV had crossed the parking lot at point A and entered the car-following zone, the participant was instructed to start driving towards its end location (point B). When the participant started driving, the TV gradually accelerated from 40 km/h to 60 km/h (speed limit of test location). As the TV reached the speed limit of the road in this section, there was not enough incentive for the participant to overtake the TV. Thus, the participant followed the TV for approximately 1-kilometre distance (~1-minute driving) at a speed of 60 km/h.

3. Overtaking: At the end of the car-following zone (recognized by the tower landmark), the TV gradually slowed down to 40 km/h, triggering the participant to overtake (Figure 2.2, bottom). The slowing down took place at one of the three randomly chosen slow-down points SP1, SP2, and SP3 (Figure 2.1). SP1 and SP3 were located 200 meters before and after the center of the landmark point (SP2). Within the overtaking zone, the participant had to decide whether and when to overtake the TV. Two types of overtaking maneuvers were identified: A flying overtaking maneuver in which the participant directly overtook the TV without the need to adjust its speed, and an accelerative overtaking when the participant followed the TV before overtaking (Hegeman, 2004). The overtaking was possible within the next 800 meters before reaching the end location of the participant. After an overtaking by the participant, the speed was restored to 60 km/h, and the TV was driven behind the participant.

Figure 2.2: (Top) Participant performing a hand gesture to indicate the last moment when she/he would decide to merge in front of the approaching vehicle. (Bottom) Start of overtaking near slow-down point (tower) from TV's rear camera perspective.

After these sequential interactions, the participant stopped at its end location point B, and the TV proceeded straight to its end location point 2. In the next run of the experiment, the participant was driven from point B to point A. In this case, the approach zone was between point 2 and point B, followed by a car-following zone and an overtaking zone. The interaction at point B was similar to point A as the TV approached from the right of the participant and drove on the opposite (farther) lane.

2.3.3. Scenarios

To observe any differences in the driving behavior of the participants during their interactions with the AV, the interaction with the TV was carried out in two scenarios. In one scenario, the TV was driven as an HDV, whereas, in the other scenario, the TV was driven appearing as an AV. In practice, in both scenarios, the TV was driven manually by the same professional driver, but in AV scenarios, the driver held the lower part of the steering wheel, while in the HDV scenarios, he held the upper part of the steering wheel, making his hands clearly visible (Figure 2.3, top vs. middle). The scenarios were named i-HDV and i-AV, where ‘i’ refers to interaction with the TV, either as an HDV or as an AV, respectively. The i-AV scenario was easily distinguishable from the i-HDV scenario by the fake LiDAR placed on the vehicle roof and a sticker saying “Self-driving” on the side of the vehicle (Figure 2.3, top vs middle). To ensure that the participants could differentiate the i-AV scenario from the i-HDV scenario, they were provided with a pre-experiment briefing, where they were shown a picture of the vehicle in i-HDV and i-AV scenarios, and an explanation on how they could notice the differences.

The experiment was designed carefully in such a way that the driving behavior of the TV in i-HDV and i-AV scenarios, was similar. The following precautions were taken to minimize differences in the driving behavior:

1. The TV was always driven by the same professional driver for all participants and in all scenarios.
2. The TV speed was kept as constant as possible in the different road sections within all scenarios, i.e., 40 km/h in the approach zone, 60 km/h in the car-following zone, and 40 km/h in the overtaking zone.
3. In case any disturbances in the speed occurred due to unavoidable circumstances, such as interaction with other road users, the data from such run were removed from the analysis.

Each participant interacted with the TV over 10 runs of which the first run was a trial run, 3 runs were i-HDV scenarios, and 6 runs were i-AV scenarios. The scenario during the first run was always i-HDV. For the rest of the 9 runs, the scenarios (i-HDV and i-AV) were randomized to counterbalance the order of encountered scenarios.

Before the last 3 runs of i-AV scenarios, positive or negative information regarding the AV behavior was provided to the participants in a written form (the information was provided only once). The type of information a participant would receive was randomly selected to achieve an equal number of positive and negative information recipients. The positive and negative information provided were as follows:

Figure 2.3: Test vehicle in i-HDV scenario (top) and i-AV scenario (middle and bottom).

Positive information: *"The self-driving vehicle you are interacting with tends to avoid risks by driving very safely. It can fully detect its environment and it is able to accurately predict the behavior of other road users, which ensures safe driving."*

Negative information: *"The self-driving vehicle you are interacting with cannot always fully detect its environment. This may cause to not correctly predict changes in its environment, leading sometimes to unsafe situations."*

Figure 2.4 summarizes the number of runs for each type of scenario.

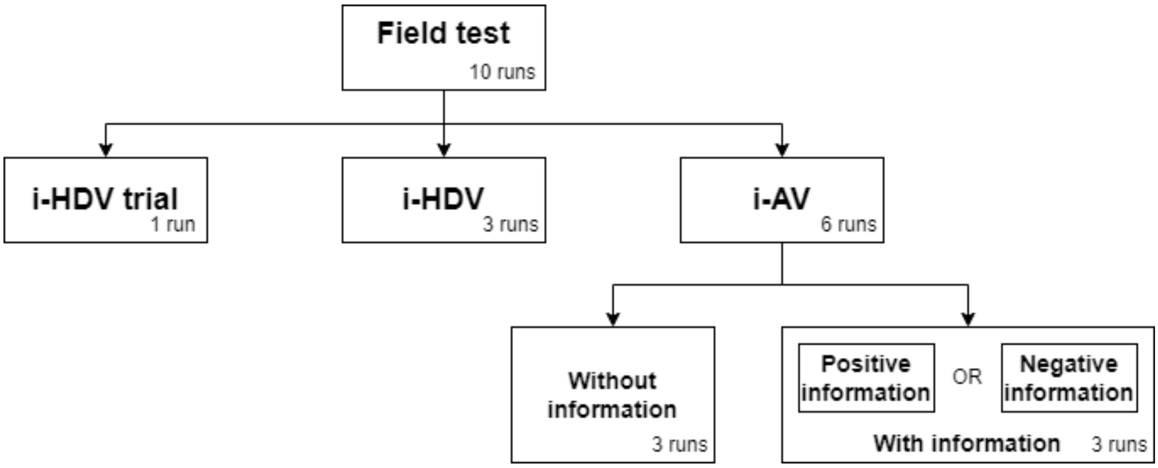


Figure 2.4: Scenario design for the field test and the number of runs for each type of scenario.

2.3.4. Vehicle and test location instrumentation

To collect data, a Toyota Prius (driven as TV) was instrumented with cameras, point Light Detection and Ranging (LiDAR) and Global Positioning System (GPS) module for data collection as shown in Figure 2.5. This vehicle was also instrumented with a detachable fake LiDAR and 'Self-driving' sticker to inform the participants whether it is driving in an AV or an HDV mode.

The point LiDARs were installed on the left, right, and rear of the TV to measure the distances of the nearby vehicles. The left and right LiDARs were installed near the rear door's handles, whereas the back LiDAR was installed on the rear bumper. The angle of the LiDARs was adjusted such that its beam stays parallel to the road surface, thus giving measurements only from reflection by objects.

To capture the video footage of the interacting participants and the surroundings, four cameras were installed on the left, right, front, and rear sides of the TV. The TV had an inbuilt GPS module that recorded the location and speed of the vehicle. A GPS module was also placed in the participant vehicle to record its location and speed.

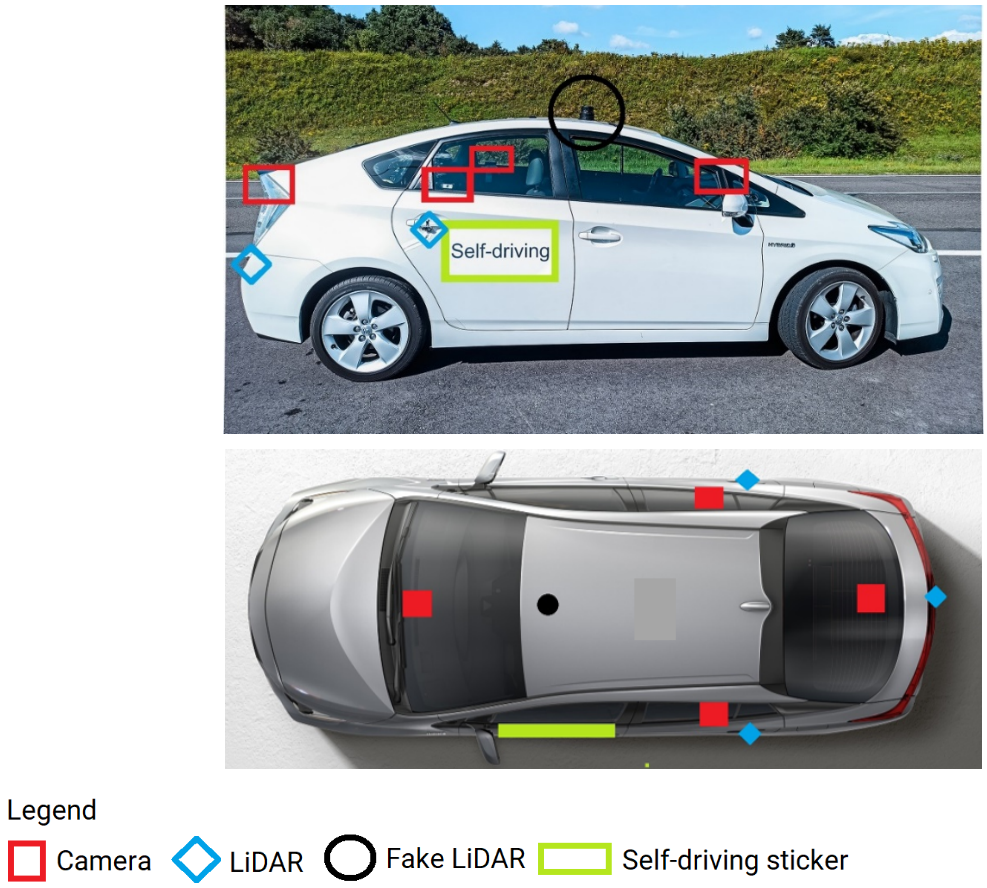


Figure 2.5: Test vehicle instrumentation. For the data collection of critical gaps, field cameras were fixed on both parking lots A and B facing towards the parking lot to capture the hand gesture of the participant indicating the last moment of merging. Also, traffic cones were placed in the approach zone to estimate the approximate distance of the TV at the time of critical gap indication (see Figure 2.6).

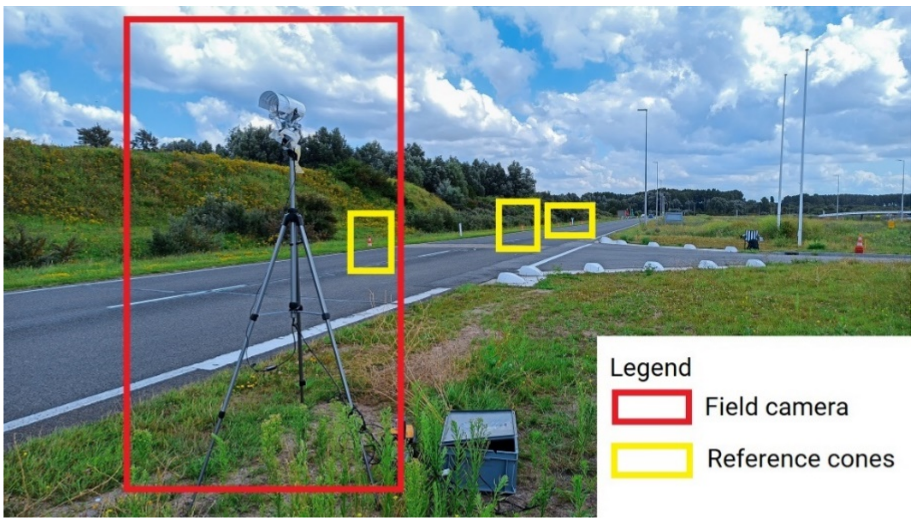


Figure 2.6: Field camera and reference cone setup near the parking lot - point B.

2.3.5. Participants

A total of 18 male participants were recruited for the field test. The participants were asked to sign an informed consent form before taking part in the experiment. Fourteen participants were between 35-60 years old, and 4 participants were younger than 35 years old. The participants were highly educated: 12 had a PhD or MSc, 4 had a BSc, and 2 had secondary education. Fifteen participants were employed full-time, out of whom 12 participants belonged to science, technology, or engineering field. The participants were experienced drivers with a minimum experience of 7 years, and 15 participants had a driving experience of more than 10 years. Several participants had driving experience with various Advanced Driving Assistant Systems (ADAS): 9 had experience with Adaptive Cruise Control (ACC), 9 with Lane-Keeping Systems (LKS), 6 with Forward Collision Warning (FCW), and 4 with Automatic Emergency Braking (AEB). One participant had experience with SAE level 2 automation.

2.3.6. Data collection procedure

Before the actual field test started, a pilot test was conducted on 14th July 2020, mostly to test the sensing equipment and the experimental procedure. After completing the pilot test, some small changes in the field test design were carried out. The final field test was carried out on 21st, 22nd, and 23rd July 2020. During these three days, the weather was clear and sunny. The traffic intensity of the test route was very low (around 30 vehicles per hour) during the field test days.

Before the field test, the participants were provided with pre-experiment questionnaires intended to collect their socio-demographics, general trust in AVs, and driving styles using the Multidimensional Driving Style Inventory (MDSI) developed by Taubman-Ben-Ari, Mikulincer, and Gillath (2004). The MDSI consists of 44 items that are ranked on a 6-point scale (‘‘not at all” to ‘‘very much”) and assesses four broad domains of driving styles: reckless and careless driving, anxious driving, angry and hostile driving, and patient and careful driving.

When the participants arrived, a briefing was provided to them, and their vehicle was equipped with a GPS module. The participants were provided with information regarding their destination and route and the speed limit of the road (i.e., 60kmph). They were asked to drive as they would normally do in real life and were told that they could perform any necessary driving maneuvers. They were not explicitly told to overtake, but the speed reduction of the TV when approaching the overtaking section (as shown in Figure 2.1) triggered the participants to overtake. At the recruitment phase, the participants were not informed that they would be interacting with AVs during the experiment; rather, that they would need to drive their vehicle from one point to another interacting with different vehicles. This was done to ensure that the participants do not build any expectations or perform any preliminary research regarding AVs before the actual field test. However, on the day of the experiment, the following measures were taken to ensure that the participants could differentiate the i-AV scenario from the i-HDV scenario:

1. The participants were briefed about how they could notice the difference between the AV and HDV vehicles, and they were shown pictures of the two vehicles that illustrate the differences (as in Figure 2.3).
2. When the experiment began, the participants started driving once they saw the TV crossing in front of them.
3. At the end of the first run with i-AV scenario, the participants were asked whether they were able to recognize the AV in contrast to the HDV.
4. At the end of the experiment, the participants were asked again in an interview if they had any difficulty recognizing the type of vehicle scenario. All the participants shared verbally that they were able to identify the type of vehicle by the fake LiDAR and sticker on the side of the vehicle.

After the briefing, the experiment started, following the field test setup previously discussed in Section 2.3.2. Other road users were also present during the experiment, which contributed to the realism in the experiment. However, the experiment was only started when other road users were not nearby. At the end of each run, the participant drove to its end location, where a team member assisted the participants in the realignment of their vehicle for the next run and reminded them to fill out the questionnaire regarding trust in the interacting TV and stress during the run. The TV drove to its end location out of sight of the participant, and it was prepared for the next run of the test by putting/removing the self-driving sticker and mounting the fake LiDAR. At the end of the experiment, the participant was provided with a post-experiment questionnaire and was interviewed for details about their observations and choices.

2.4. Data Processing and Analysis

The data processing included the processing of the sensor data and the questionnaire data.

2.4.1. Sensor data processing and analysis

The sensor data collected from multiple sources were synchronized using the timestamp indicated on the videos and the other devices. The sensor data was processed to collect various driving behavior indicators, as summarized in Table 2.2.

Table 2.2: Calculated driving behavior indicators and calculation methodology

Driving behavior	Indicator	Unit	Calculation methodology
Gap acceptance	Critical gap	s	Based on GPS distance between the participant vehicle and TV at the moment the critical gap is indicated, and the speed of the TV
Car-following	Car-following headway	s	Median of time headway during car-following
Overtaking	Overtaking duration	s	Derived from the video
	Overtaking lateral gap	m	Based on distance measured by LiDAR
	Headway at start/end of overtaking	s	Based on the distance from camera observations and GPS speed
	Relative speed during overtaking	km/h	Based on GPS speed

These indicators were calculated for each participant in each run. One observation of car-following behavior refers to the median of car-following headway for one participant for each run. To study the overtaking behavior, given its complexity, multiple indicators were defined and calculated, as illustrated in Figure 2.7. These included the headway at the start of overtaking (A), the lateral gap during overtaking when the vehicles were in parallel positions (B), and the headway at the end of overtaking (C). The start of the overtaking was defined as when the front-left wheel of the participant vehicle crossed the center line of the road, and the end of the overtaking was when the rear-left wheel crossed the center line of the road.

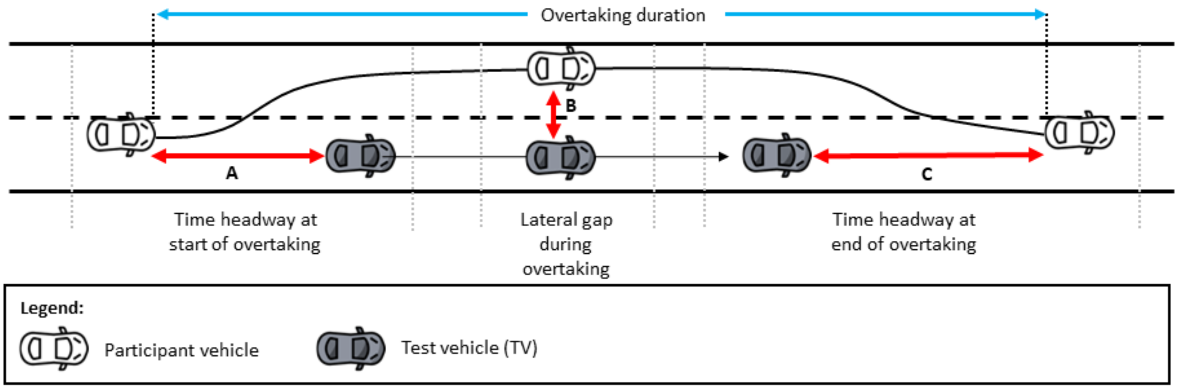


Figure 2.7: An illustration of various indicators calculated to capture overtaking behavior.

As point LiDARs were used for data collection, due to the curved vehicle front body of the participant vehicle, the light cannot always reflect to the LiDAR, leading to inaccurate readings. Thus, GPS location was used for the time headway calculation. Headways larger than 6 seconds were considered to fall within a free-flow regime and were not considered as car-following (Vogel, 2002). Each GPS sensor had an accuracy of 4 meters. Due to this high GPS error, headways at the start/end of overtaking were derived from videos manually. The lane markings of the road were used to approximate the distances.

During the data processing and calculations of the different indicators, disturbances and invalid observations such as participants failing to indicate the critical gap, disturbances by other road users, participants driving too far from the TV, and participants overtaking along with other road users were identified and removed from further analysis leading to a different number of observations per scenario and driving maneuver.

A detailed analysis of the processed dataset was carried out using descriptive statistics from which several insights regarding potential behavioral adaptation were gained. Furthermore, non-parametric statistical testing was performed to test the significance of the findings regarding drivers' behavioral adaptation.

2.4.2. MDSI questionnaire data processing and analysis

A score for each of the four driving styles for each participant was calculated based on the participants' answers, and the factor loadings provided by Taubman-Ben-Ari et al. (2004). Figure 2.8 shows the box-whisker plot of self-reported scores of the four driving styles for all 18 participants.

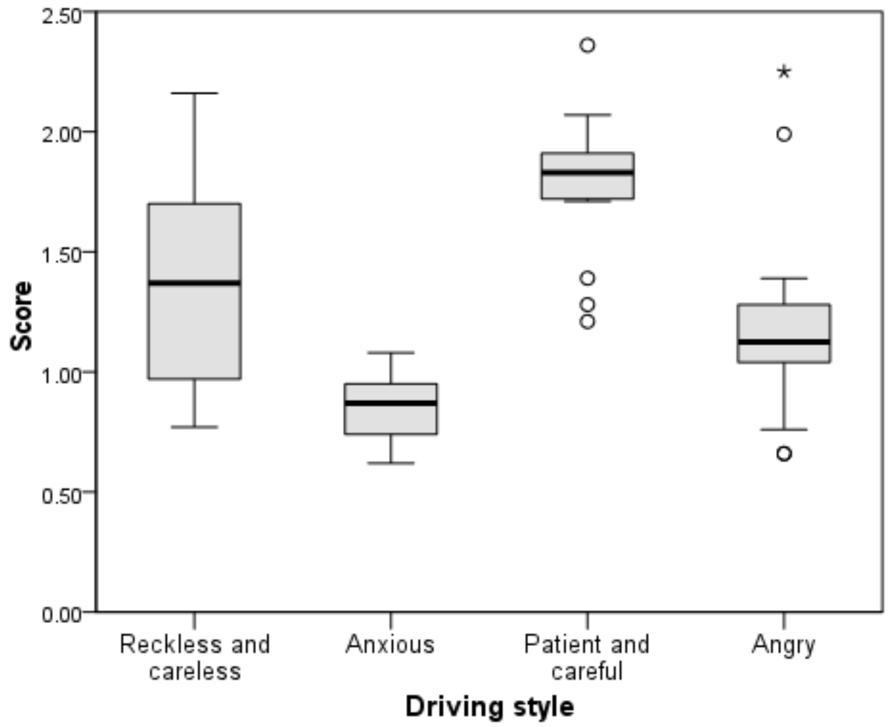


Figure 2.8: Box-whisker plot of self-reported scores falling in different driving style categories (score range 0-5).

Thus, to classify the participants based on their self-reported scores recorded for the MDSI questionnaire, a cluster analysis was carried out. The K-mean clustering resulted in 2 clusters of participants highlighting significant differences in terms of "Reckless and careless" and "Angry" driving styles. This indicated that the two clusters of participants differ in their aggression while driving, and thus, the participants were categorized into two groups: less aggressive (11 participants) and more aggressive (7 participants) drivers.

2.4.3. Drivers' characteristics as per information group

The participants were randomly assigned to the positive and negative information groups at the beginning of the field experiment. To check whether there is a significant difference in the characteristics of the drivers assigned to the two information groups, their age and driving styles were examined. No significant difference in age was found between the positive (mean age = 43.5, SD = 9.2) and negative (mean age = 41.2, SD = 10) information groups. Within the positive information recipients, there were 4 more aggressive drivers and 5 less aggressive drivers, while within the negative information recipients there were 2 more aggressive drivers and 6 less aggressive drivers. One participant who did not receive any positive or negative information due to technical difficulty during the experiment was also categorized as more aggressive driver.

2.5. Results

Table 2.3 shows the number of valid observations per driving behavior per scenario after processing the collected data. The processed data were analyzed to gain insights into the three main driving behaviors: Gap acceptance, car-following, and overtaking.

Table 2.3: Number of observations per scenario

Driving behavior	Indicator	Number of valid observations per scenario				Total
		i-HDV*	i-AV*			
			No info	Positive info	Negative info	
Gap acceptance	Critical gap [s]	69	51	24	23	167
Car-following	Car-following headway [s]	53	40	14	21	128
Overtaking	Overtaking duration [s]	53	39	18	22	132
	Overtaking lateral gap [m]	48	35	15	22	120
	Headway at start of overtaking [s]	51	38	19	22	130
	Headway at end of overtaking [s]	51	38	18	22	129
	Relative speed during overtaking [km/h]	52	38	19	22	131

* i refers to interaction with the test vehicle

2.5.1. Gap acceptance behavior

Figure 2.9 presents a boxplot of the indicated critical gaps of different participants in i-HDV and i-AV scenarios. It can be seen that the observed indicated critical gaps vary between the i-HDV and i-AV scenarios for the same individual. Due to differences in driving styles and personal characteristics, variation among the indicated critical gaps was also found between participants.

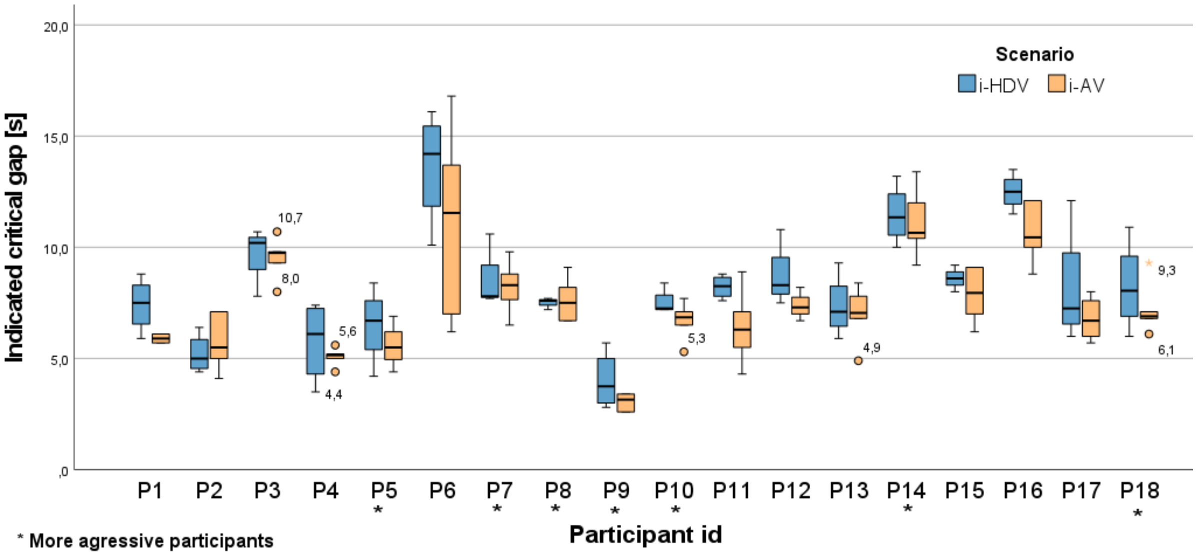


Figure 2.9: Participants' indicated critical gaps in both scenarios i-HDV and i-AV.

Figure 2.10 (left) shows the boxplot of the indicated critical gaps in i-HDV and i-AV scenarios for all participants. The mean indicated critical gap in i-AV scenarios is significantly smaller than i-HDV scenarios (Wilcoxon Signed Ranks test, $Z\ value = -3.419, p-value = 0.001$).

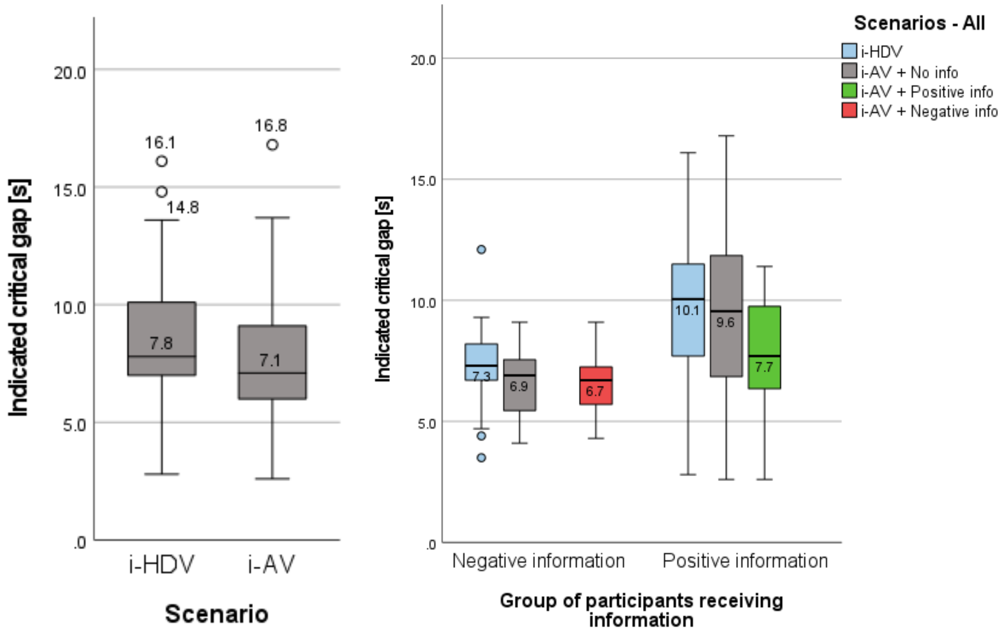


Figure 2.10: Boxplot of average indicated critical gaps for 18 participants in i-HDV and i-AV scenarios (left) and within different information groups (right).

Figure 2.10 (right) shows the boxplot of the indicated critical gaps of participants receiving negative and positive information. The mean indicated critical gap was also found significantly smaller in i-AV scenarios without information in comparison to i-HDV scenarios (Wilcoxon Signed Ranks test, $Z\ value = -5.232, p - value = 0.001$). The indicated critical gap values differ marginally between the two groups because of individual differences between the participants that belong to each group. The group receiving positive information is more balanced in terms of an equal number of more and less aggressive drivers, potentially leading to a wider spread of critical gap observations. However, the group receiving negative information is primarily dominated by the less aggressive participants, leading to less spread in critical gap observations. It was expected that the less aggressive drivers which mostly dominate the negative information group would accept larger critical gaps in comparison to the more aggressive drivers especially in i-HDV and i-AV + No info scenarios. However, the results in Figure 2.10 (right) show the opposite trend. This counterintuitive observation could be due to small numbers of participants in each of these groups.

To test the effect of information, Wilcoxon signed ranks test was performed to compare the indicated critical gaps in the i-AV scenario just before providing information and just after providing information. It was found that the indicated critical gaps decreased significantly just after providing positive information (Wilcoxon Signed Ranks test, $Z\ value = -2.033,\ p - value = 0.042$) (Figure 2.10, right). However, no significant difference was found for the group that received negative information (Wilcoxon Signed Ranks test, $Z\ value = -1.014, p - value = 0.310$). Figure 2.11 illustrates this again, but for each interaction. For i-AV scenario, there was also a significant difference in the mean indicated critical gap between positive and negative information groups (Wilcoxon Signed Ranks test, $Z\ value = -3.621$, $p - value < 0.001$).

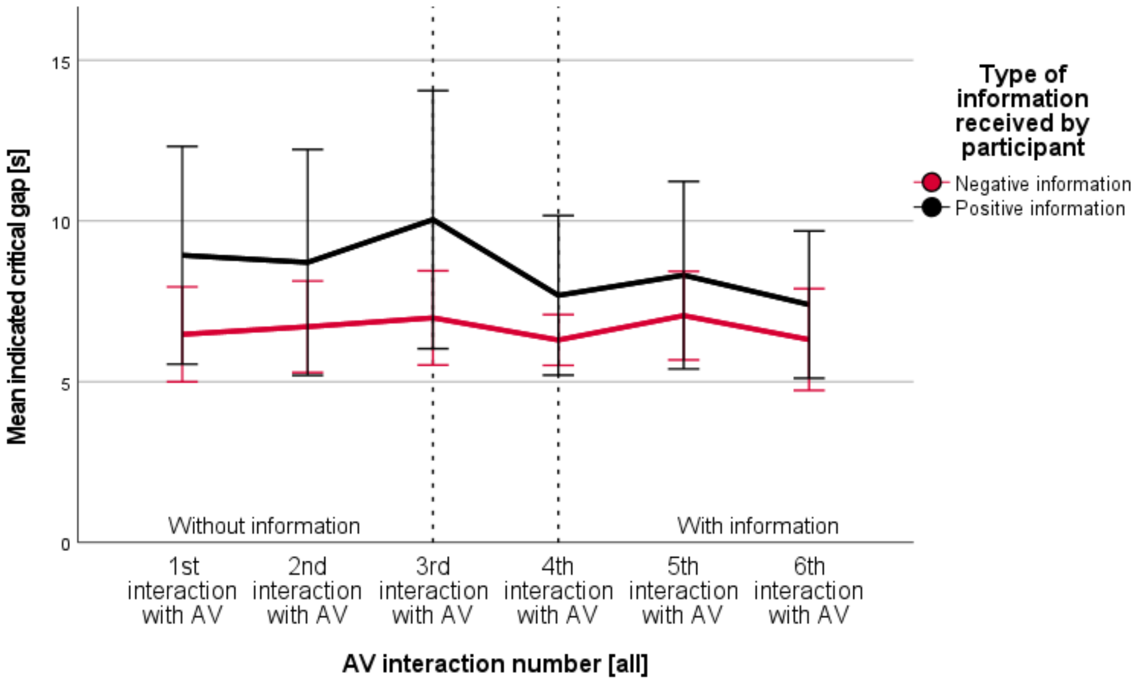


Figure 2.11: Indicated critical gap per interaction with AV for different information groups

The more aggressive driver group showed a reduction in the mean indicated critical gaps during their interactions with the AV. A significant negative correlation was found between the mean indicated critical gap and the mean reported trust in the AV over the multiple interactions (Pearson's $r = -0.343$, $p - value = 0.032$, $N = 39$). However, in contrast, no significant correlation was found between their mean indicated critical gap and their mean reported trust when interacting with the HDV ($r = -0.326$, $p - value = 0.104$, $N = 26$). A similar correlation for the less aggressive drivers was observed during their multiple interactions with the AV ($r = -0.372$, $p - value = 0.004$, $N = 58$). However, this group also showed a significant negative correlation between the mean indicated critical gap and the mean reported trust when interacting with the HDV ($r = -0.316$, $p - value = 0.039$, $N = 43$).

2.5.2. Car-following behavior

In order to gain insights into the car-following behavior, median time headway during car-following was calculated for each participant and scenario. The speed profile of the TV was kept similar within all the scenarios. From the GPS analysis in the car-following zone, it was observed that the speed of the TV in the i-HDV scenario (mean = 52.3 km/h, median = 53.8 km/h, SD =8.9 km/h) was very similar to the speed in the i-AV scenario (mean = 53.4 km/h, median = 54.8 km/h, SD = 6.7 km/h). Figure 2.12 shows the scatter plot and box and whisker plot of car-following headway observations for all participants in different scenarios. From the plots, it can be seen that half of the participants maintained higher headways with AVs than with HDVs, while the other half had the opposite trend. No statistically significant difference was found in car-following behavior between the two scenarios (Wilcoxon Signed Ranks test, $Z\ value = -0.355, p - value = 0.722$).

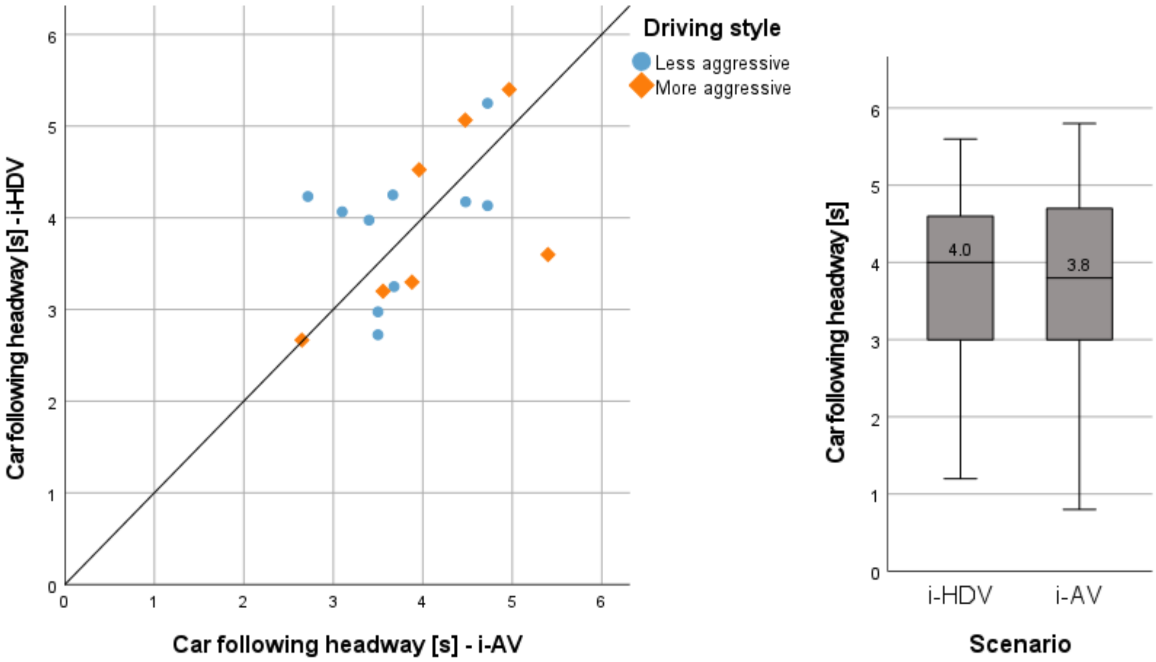


Figure 2.12: Scatter plot (left) and boxplot (right) of median car-following headways in different scenarios (sample size is 17 as one participant had missing data).

2.5.3. Overtaking behavior

Overtaking behavior was studied in terms of overtaking duration, overtaking lateral gap, relative speed during overtaking, headway at the start of overtaking, and headway at the end of overtaking. Mainly two different overtaking styles were observed during the experiment: flying and accelerative. Flying overtaking was witnessed more frequently than the accelerative overtaking style.

A significant difference was observed in the overtaking behavior in terms of headways at the end of overtaking between AVs and HDVs. Figure 2.13 presents the analysis of the mean time headway at the end of overtaking over the multiple interactions with the AV before and after receiving the information regarding the AV. It can be observed that the participants adopted significantly lower headways at the end of overtaking maneuvers of the AV (mean = 1.3 s) in the case of positive information scenario in comparison to the no-information scenarios (mean = 1.7 s) (Dunn's pairwise test, $Z\ value = 19.625, p - value = 0.007$), while for negative information, no significant difference was found (Dunn's pairwise test, $Z\ value = 8.375, p - value = 0.997$).

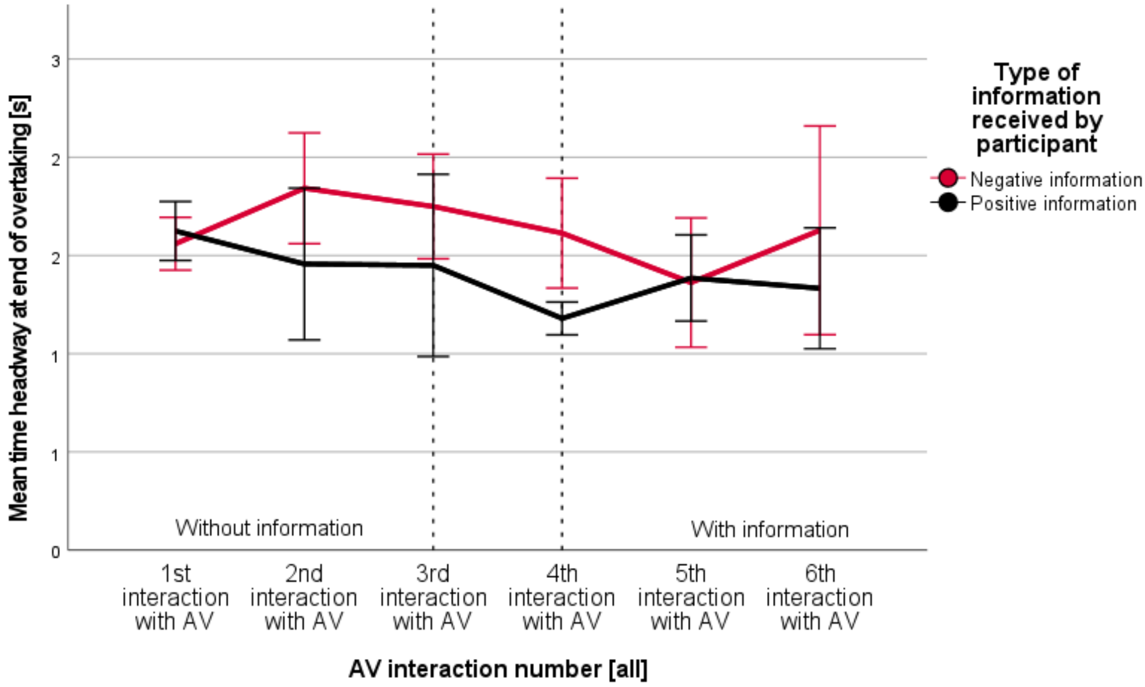


Figure 2.13: Headway at the end of overtaking over multiple interactions with AV (within information groups) (Error Bars: 95% CI; Sample size = 17)

Also, headways at the end of overtaking maneuvers decreased over consecutive interactions with AVs (Figure 2.14) within the accelerative overtaking style ($r = -0.509, p-value = 0.005, N = 29$), while for the flying overtaking style, no significant difference was found ($r = -0.051, p-value = 0.728, N = 49$).

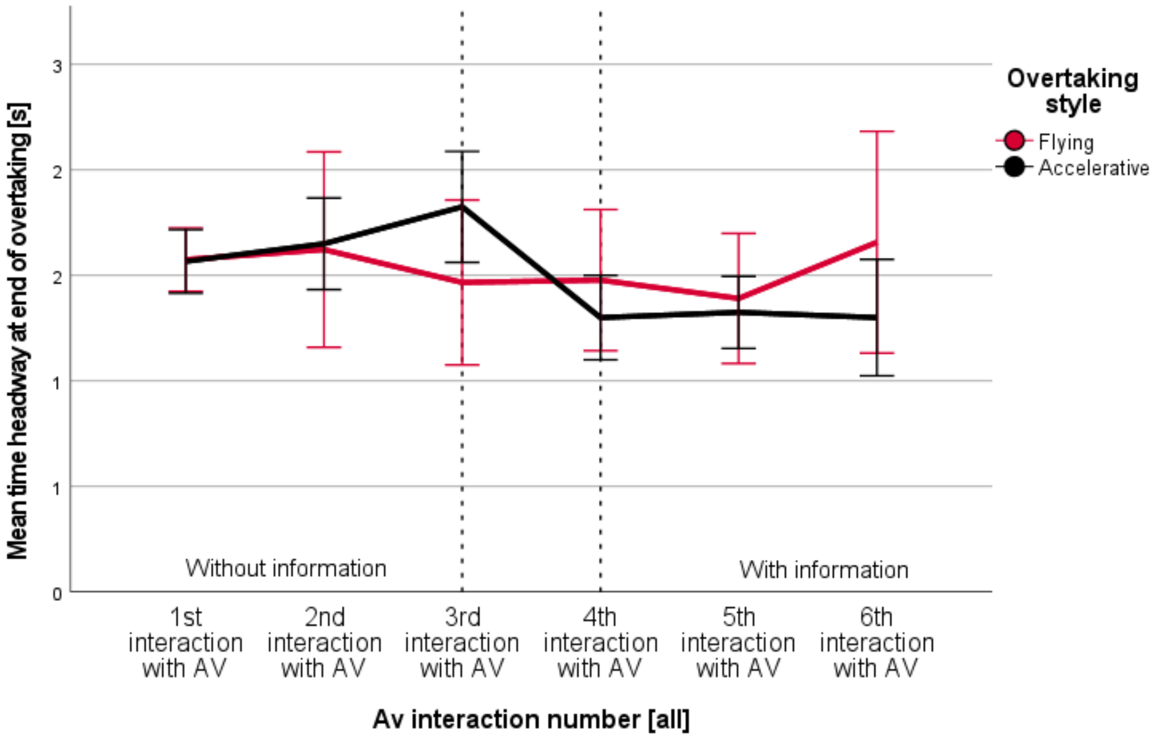


Figure 2.14: Headway at the end of overtaking maneuver over multiple interactions with AV (Within different overtaking styles) ; Error Bars: 95% CI; Sample size = 17

2.5.4. Trust

To study the effect of trust within scenarios of different information, Wilcoxon signed ranks tests were performed. No significant difference was observed in the reported trust between AV and HDV scenarios ($Z\ value = -0.028, p - value = 0.977$). Within the group that received positive information, it was found that the reported trust was significantly higher in i-AV scenarios after providing positive information (Mean = 8.4, SD = 1.5) in comparison to the reported trust in scenarios before receiving this positive information (Mean = 7.9, SD = 2.2), ($Z\ value = -2.117, p - value = 0.034$). However, no significant difference in trust was seen for the participants receiving negative information (Mean = 8.2, SD = 2.1) in comparison to the reported trust in scenarios before receiving this negative information (Mean = 8.0, SD = 2.0), ($Z\ value = -0.137, p - value = 0.891$).

2.6. Discussion

In this study, the behavioral adaptation of human drivers when encountering AVs was observed in terms of gap acceptance and overtaking behavior but not in car-following behavior. For gap acceptance behavior, it was observed that the critical gap of drivers significantly decreased when they interacted with AVs compared to when they interacted with HDVs. This decrease in the critical gap was more prominent when positive information on the AV behavior was provided to the participants in comparison to no information. A similar impact was found for the headways at the end of overtaking maneuver, with the headway significantly decreasing when positive information regarding the interacting AV was provided. Therefore, positive information regarding the AV played a role in that drivers had smaller critical gaps and maintained significantly shorter headways at the end of overtaking. For the accelerative overtaking style, the headways at the end of overtaking decreased significantly with multiple interactions with the AV. For car-following behavior, there was no significant difference in the median headway when following an AV compared to when following an HDV. Furthermore, there were no significant differences in the overtaking duration, overtaking lateral gap, headway at the beginning of the overtaking, and the relative speed during overtaking.

The key finding of this research is that both interactions, gap-acceptance and merging back into the lane at the end of overtaking, are similar in the sense that the participants interacted with AVs in the "forward field of view" of the AV. These interactions differ from the other examined interactions (car-following, lateral gap, speed during overtaking, and headway at the beginning of overtaking) in that during the latter interactions, the participants have more control of the situation in terms of actively performing safe maneuvers and are responsible for maintaining safe distances from the test vehicle. However, in the former interactions, since the test vehicle drives behind the subject vehicle, the participants expect the test vehicle to take more control of the situation and maintain safe distances. The consistency of these findings further enhances the presence of behavioral adaptation.

The finding of no significant difference in the car-following behavior of drivers is opposite to findings from previous studies, which indicated that HDV drivers reduced their car-following headways while interacting with AVs or a platoon of AVs (Gouy, 2013; Gouy et al., 2014; Rahmati et al., 2019; Schoenmakers et al., 2021; Zhao et al., 2020). This could be due to the low accuracy of GPS sensors in this study or the relatively simple test environment. Also, the experiment was designed to maintain a constant speed of 60 km/h during car-following, which made it difficult to study car-following headways during different speed regimes. Therefore, further research is needed.

No significant difference was observed in the reported trust between AV and HDV scenarios. However, within the group that received positive information, it was found that the reported trust was significantly higher in i-AV scenarios after providing the positive information, while this was not the case for the negative information. This could indicate a possible interaction effect between trust and information. From the analysis, it was observed that trust and information are two significant factors influencing the critical gap of the participants. While the positive information seem to significantly decrease indicated critical gap, trust also has a significant negative correlation with indicated critical gaps of participants interacting with AVs, especially for more aggressive drivers. As AVs are expected to be designed to interact safely and to drive defensively, these findings indicate potential exploitation of the technological advantages of AVs by the road users for their advantage.

Half of the participants in this study were also provided with negative information regarding the interacting AV. However, no significant effect of negative information was observed in their driving behavior and trust. One possible reason for this is the presence of a driver inside the test vehicle. The participants said that they were confident regarding the safety as a driver was always present for takeover in case something goes wrong. Another factor indicated by the participants is the simplicity of the test environment - the road having low traffic volumes, clear lane markings, and clear weather - in which it is less likely for the AV to fail with its environment detection.

The findings of this research are in line with some findings in the literature. A driving simulator study by Trende et al. (2019) found that human drivers accepted more frequent gaps when interacting with AVs than HDVs and suggested that AVs can be technologically exploited by the HDV users for their advantage, which is in line with our findings. The studies relating to lane change behavior indicated an increase in lane change duration while driving near a platoon of AVs (Lee & Oh, 2017; Lee et al., 2018). However, we did not observe any difference in terms of overtaking duration while interacting with the AV. This could be because we studied the interactions with one AV and not a platoon of AVs. Thus, an increase in overtaking duration may be attributed to higher penetration rates of AVs where platooning is possible. The only significant difference was observed in terms of headways at the end of overtaking, which indicated closer interactions with AVs.

AVs are perceived to have a greater ability to respond and are expected to take more control in performing safe driving interactions. This is also corroborated by the findings in Trende et al. (2019). With positive information, the trust in AV further increased and drivers had closer interactions with the AV. From a behavioral adaptation perspective, it can be concluded that closer (and more opportunistic) interactions with AVs can be expected in comparison to HDVs. More specifically, smaller gaps in front of the AV will be accepted. Thus, there is a potential for exploitation of AVs technology by human drivers, and more abrupt merging (cut-offs) can be expected with AVs. For interactions from the rear and sides of the AV, no significant difference in driving behavior is expected based on the results of this study.

One immediate implementation of the results from this research is to investigate the effect of this behavioral adaptation on traffic flow and safety by using the empirical findings to adapt the parameters of the behavioral models in microscopic traffic simulation.

Various other factors such as age, driving experience, education, reported stress during the run, reported stress in different maneuvers, and weather were also taken into account for the analysis of behavioral adaptation. However, most of the participants had similar personal characteristics. In addition, the weather was sunny on the days of the experiment. The participants were also asked about their stress levels (on a scale of 1 to 10) while performing different maneuvers. However, most of them did not report any differences in the stress between different scenarios.

Therefore, the variation within these factors was not sufficient to observe any statistically significant differences in driving behavior.

2.7. Research limitations and future work

In this research, there are few limitations. First, in order to ensure that human drivers could clearly recognize the AV during the interaction based on its physical features (fake LiDAR and sticker on the side of the vehicle), pre-experiment briefing was provided to the participants. However, recognizability of AV without providing any information is still questionable and needs to be investigated in future studies. Second, the sample of participants is not representative of the population as all the participants were male and experienced drivers. Also, the participants were mostly from the background of science and technology and therefore were capable of better understanding the technology of AVs. Therefore, it is recommended to investigate the behavior of groups of participants with a non-technological background.

Another area of future research is to study the effects of other influencing factors such as human drivers' characteristics, subject vehicle characteristics, and external factors on the change in driving behavior. Statistical models can be designed to identify the effect of individual or groups of factors contributing to behavioral adaptations. These models then can be implemented in microscopic traffic simulations to investigate the effect of such behavioral adaptations on traffic flow and safety. Furthermore, more data need to be collected to take into account different driving behaviors of AVs, absence of a driver in AVs, different road types and speed limits, the presence of other road users, different recognizability of AVs, and different environmental conditions such as weather, time of day, visibility, to cover the entire spectrum of behavioral adaptation with AVs. These factors may have a major influence on the decisions of HDV drivers. Additionally, behavioral adaptation is more associated with long-term interactions, and it is important to study various effects over longer periods. Thus, more field tests (and in more naturalistic settings) need to be conducted.

2.8. Authorship contribution statement

Shubham Soni: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Project administration. Nagarjun Reddy: Conceptualization, Methodology, Writing – review & editing, Supervision. Anastasia Tsapi: Conceptualization, Writing – review & editing, Supervision, Funding acquisition. Bart van Arem: Writing – review & editing, Supervision. Haneen Farah: Conceptualization, Methodology, Writing – review & editing, Supervision, Funding acquisition.

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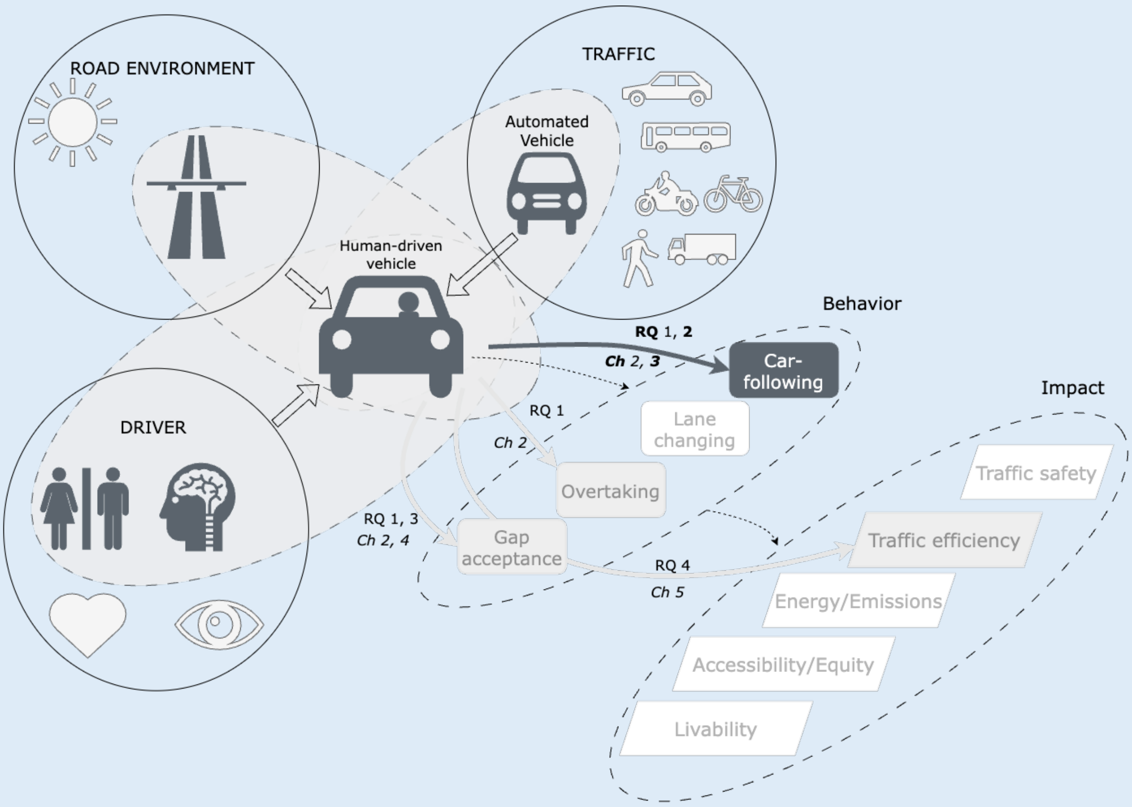
Chapter 3

Investigating car-following behavior: A driving simulator experiment

In Chapter 2, we found first evidence that human drivers experience behavioral adaptation in mixed traffic. In Chapter 3, we focus on car following behavior. A driving simulator experiment is set up where drivers follow a lead vehicle appearing either as an automated vehicle or human-driven vehicle. In addition, we estimated the Intelligent Driver Model (IDM) and the IDM+ to get insights into driving behavior parameters.



Highlights

- Human drivers' car following behavior in mixed traffic was studied in a driving simulator experiment.
- Drivers have smaller desired velocity, smaller jam spacing, and smaller safe time headway when the leader's appearance is AV compared to HDV.
- AV driving style of leader results in smaller desired velocity than HDV driving style
- When leader follows AV driving style, the desired velocity is larger for drivers having greater trust in AVs.

This chapter is based on the [submitted for publication] paper: Reddy, N., Hoogendoorn, S. P., & Farah, H. (2024). *Investigating car-following behavior: A driving simulator experiment.*

Chapter 3
Table of Contents

3. Investigating car-following behavior: A driving simulator experiment

3.1. Introduction

In recent years, AVs have been the focus of the public, the automotive industry, and the research discourse due to their several expected benefits in terms of traffic safety, traffic flow efficiency, accessibility, and environmental impact (Greenblatt & Shaheen, 2015; Piao et al., 2016). Despite this, the pace of their deployment on public roads has been slow and gradual. This is not unexpected as along with their anticipated benefits, many challenges are associated with their deployment, among these safety concerns stand out. Crashes involving AVs on public roads (Favarò et al., 2017) have raised caution and increased skepticism towards what would really be the impact of AVs on public roads, especially when operating alongside and interacting with human-driven vehicles (HDVs) and with vulnerable road users (e.g., cyclists, pedestrians). Investigations into crashes involving AVs revealed that AVs have more than double the crash rate than conventional vehicles (Schoettle & Sivak, 2015). Another study reported that the most occurring type of crash between AVs and HDVs is when the AV is at standstill while the HDV is moving straight behind the AV, resulting in rear-end collisions (Xu et al., 2019). The reason was said to be the sudden braking of the AV when encountering situations such as pedestrian crossing the road, which the following HDV driver fails to take timely notice of.

There is a need to investigate the impact of AVs' deployment on public roads on mixed traffic (traffic containing AVs and HDVs) safety and efficiency. A critical part of this investigation involves studying the (microscopic) interactions between AVs and HDVs. Studying these interactions would provide insights into the effects of AVs on the behavior of HDVs, and vice versa. These interactions could generally be characterized in, for example, car-following behavior, or lane changing behavior. Such mathematical models are currently, however, scarce. There is a lack of HDV models that consider mixed traffic-specific factors. Moreover, there is not yet a clear understanding of the need for models dedicated to mixed traffic conditions. To address these shortcomings, we focus in this paper on car-following behavior of HDVs when following AVs.

3.2. Literature Review

This chapter presents first the literature with respect to car-following behavior, followed by a review of studies that focused on the effects of AVs on HDVs, and ends with the identified research gaps and research questions

3.2.1. Car-following behavior

Car-following refers to a vehicles' longitudinal driving behavior, describing how a vehicle follows its leader, including how responsive/sensitive it is to its leader's (changing) state. The scientific literature contains several models to describe the car-following behavior. Several researchers have already conducted extensive review studies and discussions on the various car-following models (Aghabayk et al., 2015; Brackstone & McDonald, 1999; Y. Li & Sun, 2012; Saifuzzaman & Zheng, 2014). Saifuzzaman & Zheng (2014) broadly classifies car-following models as having two perspectives: engineering perspective and human factors perspective. Models such as Gipps (Gipps, 1981), Intelligent Driver Model (IDM) (Treiber et al., 2000) , Optimum Velocity (OV) (Bando et al., 1995), and Nagel-Schreckenberg (Nagel & Schreckenberg, 1992) fall under the engineering perspective, and models such as Wiedemann (Wiedemann, 1974), visual angle (Michaels, 1963), prospect theory fall (Kahneman & Tversky, 2013) under the human factors perspective as in addition to observable external traffic engineering aspects such as distance spacing and speed difference, these models include aspects such as human decision making process or mechanisms of visual perception. Studying and discussing these various existing models is out of the scope of this paper.

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

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

3.2.2. Impact of AVs on HDVs

Empirical based studies have investigated the impact of AVs on car-following behavior of HDVs in mixed traffic and have found evidence for modifying HDVs' car-following behavior. These studies employed different research methodologies, including driving simulators, field test experiments, and naturalistic driving datasets.

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

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

3.2.3. Research gaps and research questions

The evidence that there is indeed an impact of AVs/mixed traffic on car-following HDV behavior is at a nascent stage. Research studies have only recently started to explore this issue. They have found that HDVs do adapt their car-following behavior due to interactions with AVs (Aramrattana et al., 2022; de Zwart et al., 2023; Mahdinia et al., 2021; Razmi Rad et al., 2021;

Wen et al., 2022; Zhao et al., 2020). However, the precise nature of these impacts and their contributing factors is still vastly unexplored. Therefore, there is a need to further investigate the impact of AVs on HDVs' car-following behavior.

Moreover, microscopic simulation studies use car-following models to describe HDVs' longitudinal behavior in mixed traffic. However, most of these studies use the same HDV models that are used and calibrated for conventional traffic. This remains an assumption that still needs to be validated. Especially that some empirical studies have found evidence that human drivers do change their behavior when interacting with AVs and interact differently with these vehicles compared to when interacting with HDVs. We found only two simulation studies (Hua et al., 2020; Li et al., 2023) that implemented different HDV models depending on whether the leader was an HDV or AV, thus recognizing that there is HDV behavioral adaptation. However, they do not provide empirical evidence for the specific changes they make. Also, it leaves open the question of how does do models with modified HDV behavior compare to not having modified HDV behavior. Hence, there is a need for HDV models that consider mixed traffic-specific factors. Or at least, there is a need to investigate whether such modified HDV models are significantly/meaningfully different from the HDV models in conventional traffic. Such new HDV models could be developed either by making some informed assumptions on the parameters of existing models, by calibrating the models using empirical data, or by designing completely new models (S. Calvert et al., 2017) .

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

1. How can car-following model parameters capture the changes that occur in the behavior of HDVs in mixed traffic?
2. How does the choice of the car-following model affect the measured impact of mixed traffic on HDV car-following behavior?
3. What is the effect of mixed traffic on car-following behavior of HDVs?

3.2.4. General approach and outline of the paper

We take the following approach to address the research questions. First, we collect empirical data on drivers' car-following behavior in mixed traffic through a driving simulator experiment. Then, to capture the observed behavior mathematically, we estimate car-following models to describe the observed car-following behavior in the different scenarios. Finally, we estimate regression models for the estimated car-following parameters to gain insights into the specific factors affecting these parameters, which ultimately provide understanding on the effect of mixed traffic factors on car-following behavior of HDVs.

The rest of the paper is structured as follows. Section 3.3 describes the set-up of the experiment (data collection). Section 3.4 discusses the estimation of the car-following models and findings. Section 3.5 presents the estimated regression models for the parameters. Section 3.6 discusses all the results, organized by the research questions, and the limitations. Finally, Section 3.7 presents the conclusions and recommendations.

3.3. Experiment set-up and data collection

3.3.1. Apparatus

A driving simulator experiment was designed to collect data on the car-following behavior of HDVs in the different scenarios. The driving simulator used (Figure 3.1) is located at the Transport & Planning department of Delft University in the Netherlands. It operates using the

SCANeR (v1.9) software by AV Simulation. It is a fixed base driving simulator equipped with a Fanatec steering wheel and pedals, a dashboard mock-up, and three 4 K high-resolution screens which approximately provide 180° vision.

Figure 3.1:The driving simulator used for data collection

3.3.2. Protocol and Questionnaires

After the approval from the Human Research Ethics Committee of TU Delft, participants were recruited with the support of the Municipality of Delft, with a selection process ensuring an age and gender balance. A valid driving license was needed to participate in the experiment. Prior to the driving simulator session, participants filled in questionnaires to collect their demographics, and driving style (MDSI – which consists of 44 questions that allows to score drivers on different driving styles such as Reckless, Anxious, Angry, and Careful) (Taubman-Ben-Ari et al., 2004). We also had questions to measure their trust in technology (Hagenzieker et al., 2020; Merritt et al., 2013), trust in AVs (Payre et al., 2015), Knowledge of AVs, and Experience with AVs. For the Knowledge and Experience with AVs, the participants were asked to rate their knowledge about and experience using the following systems on a 6-level scale: Cruise Control, Lane Departure Warning, Adaptive Cruise Control, Lane-Keeping Assist, Lane Change Assist, and Forward collision-avoidance. On arrival at the experiment room, participants were asked to read the information sheet and to sign the consent form. Then, the researcher instructed them on the driving simulator equipment and guided them through a familiarization drive (which generally lasted around 8 minutes). When the participants felt comfortable, the experiment began where participants drove 4 different scenarios, with adequate breaks in between. On average a scenario took about 10 minutes. After the driving simulator experiment, participants filled in two additional questionnaires to measure their simulation sickness (only 2 participants had to stop earlier due to simulation sickness) and realism in the driving simulator environment. Every participant received a compensation of 15 euros as a gesture of gratitude at the end of the experiment.

3.3.3. Route

Drivers followed a route that consisted of 3 parts. Part 1: 3 motorway on-ramps (excluding an initial on-ramp), Part 2: 3 provincial road signalized intersections, and Part 3: a straight road section. Figure 3.2 depicts the route. The scope of this study is limited to Part 3, the straight road section (single lane, about 5.5 km long), focusing on car-following behavior.

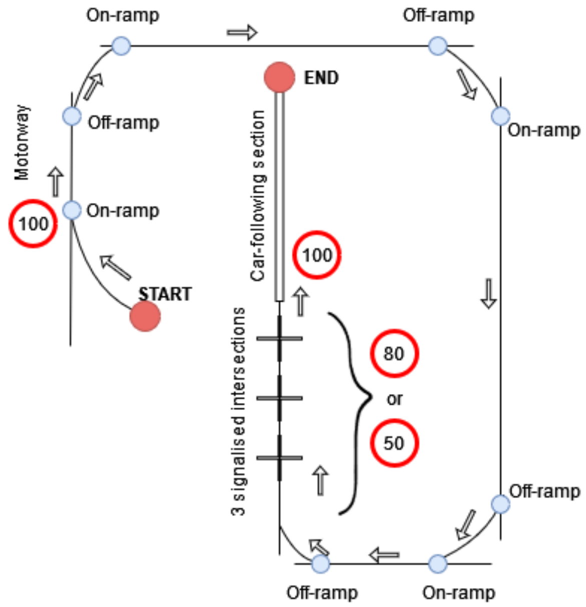


Figure 3.2: Sketch of the route developed in the driving simulator.

3.3.4. Scenarios

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

Each driver drove four scenarios, excluding an initial familiarization scenario. The four scenarios varied in terms of the appearance of the vehicle interacting with the human driver and its driving style as shown in Table 3.1. The AV was chosen to be white colored because the white color for vehicles has a relatively neutral score on aggressiveness scales (Davies & Patel, 2005). If for some reason, the participant had to stop mid-way (due to error in following the instructions, or simulator technical issues), then that scenario would be repeated starting from the next Part. For example, if a scenario was stopped in Part 2 (due to technical issues), then the participant would drive the same scenario but starting from Part 3. We noted this under a variable "Trial". A participant could therefore do multiple "trials" for the same scenario. It is to be noted that multiple trials rarely occurred.

Table 3.1: Scenarios with their appearance and driving styles of the interacting vehicle

Scenario code	Appearance	Driving Style
HDV HDV	HDV	HDV
HDV AV	HDV	AV
AV AV	AV	AV
AV HDV	AV	HDV

3.3.5. Vehicle behaviors

Globally, we classified the behavior of the interacting vehicle as HDV style or AV style. In the route prior to the car-following section, the interacting vehicles drove differently as per the scenario. In general, AV driving style meant strictly following the speed limit and maintaining consistent and constant time headways (decided based on ACC settings found in several commercial car manuals). HDV driving style meant slightly exceeding speed limit and varying time headways (derived from real world data on provincial roads provided by the Province of Noord Holland). When the participant merged to the motorway from an on-ramp, AVs approaching the on-ramp on the motorway maintained a fixed time gaps of 2 s, while HDVs had alternating gaps of 1 s, 2 s, and 3 s. This is important to note as even though the scope of this paper is limited to the car-following section, drivers experience the conditions of the scenario (their interactions with AVs or HDVs) earlier in the route which could affect the way they drive in the car-following section.

The car-following section consisted of a single lane road, and a platoon of 4 vehicles was preplaced, where the lead vehicle (vehicle 4) was defined to follow a specific speed profile. The other vehicles' desired velocities being larger than the speed limit ensured they follow the lead vehicle actively. The last vehicle in the platoon (vehicle 1) became the lead vehicle for the participating driver. Vehicle 1's appearance was as HDV or AV as per the scenario, with no other difference. We designed the speed profile for vehicle 4 aiming at a "complete trajectory", considering the need for calibrating a car-following model (Sharma et al., 2018). Figure 3.3 shows the 2 speed profiles of the lead vehicle experienced by drivers. Drivers encountered one of these 2 speed profiles randomly, to prevent anticipation.

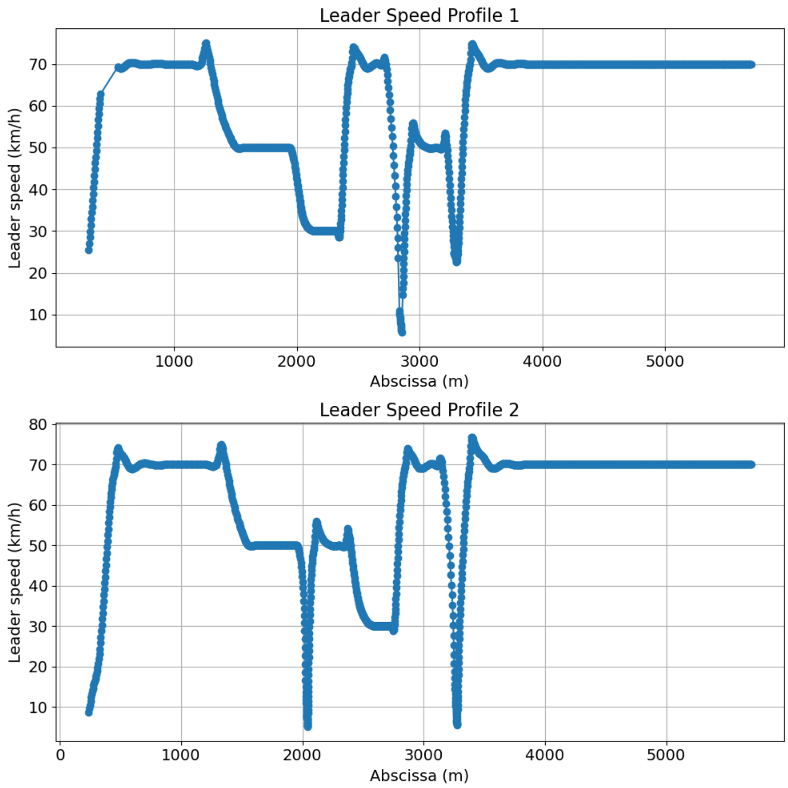


Figure 3.3: The two speed profiles of the lead vehicle.

3.3.6. Data export and handling

The simulator allows the export of data per scenario. This data consists of state variables of every vehicle in the scenario. State variables include vehicle ID, timestamp, position, speed, acceleration, lane ID, et cetera. We first exported the data at a frequency of 4 Hz (4 observations every second), which is sufficient for this type of analysis. Then, we renamed the data files to code using the participant numbers and scenario numbers. After that, using the road IDs, we filtered the dataset only for the car-following road section, and using vehicle IDs, we extracted only the lead vehicle and subject vehicle state variables. Furthermore, we filtered the dataset for relevant state variables only, namely, vehicle ID, position, speed, acceleration, lane ID, lane abscissa (position of vehicle in the lane along curvature), and timestamp. Using state variables that describe the vehicle positions and speeds, we calculated the space and time headways of the subject vehicle. Finally, this resulted in a dataset that consisted of all the state variables (those obtained directly from the simulator and the ones we calculated), for all drivers, for all scenarios. We also included the order in which drivers encountered the scenarios in the dataset. The final dataset consisted of 204164 observations, for 47 participants.

3.3.7. Participants

In total 47 drivers took part in the driving simulator experiment. We categorized them into three age categories. There were 16 younger (25 - 45) drivers (8 male, 8 female), 16 middle-aged (45 – 65) drivers (8 male, 8 female), and 15 older (70+) drivers (10 male, 5 female). In general, there was a relatively good representation of the different age and gender groups. Figure 3.4 shows the driving style distribution across all the drivers, calculated from the MDSI driving style evaluation questionnaire. One thing that stands out is that most drivers have a higher extent of the Patient and Careful driving style.

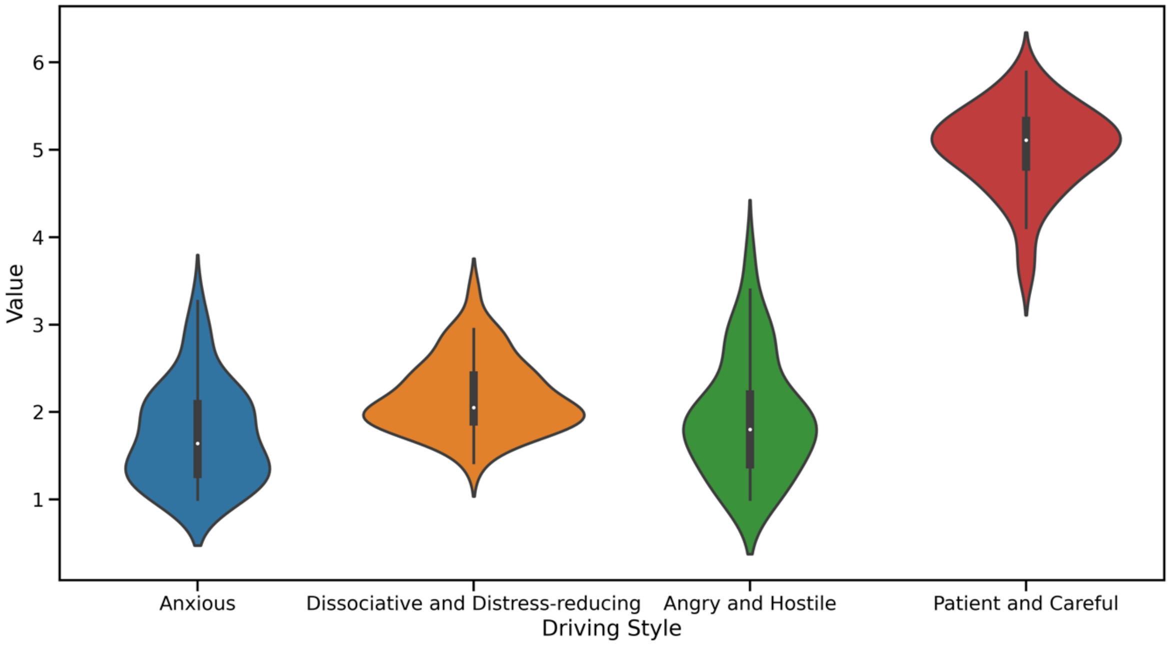


Figure 3.4: Participants' driving styles distribution (violin plot) calculated from the MDSI driving style evaluation questionnaire.

3.4. Estimation of car-following model

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

3.4.1. Model selection

We selected the Intelligent Driver Model (IDM) (Treiber et al., 2000), and its adapted version, the IDM+ (Schakel et al., 2010) as the car-following models to be investigated in this study. The IDM is a frequently used model that considers both the desired velocity and the desired space headway of the driver; and is known to perform relatively well when compared to observed car-following behavior (Punzo et al., 2021; Saifuzzaman & Zheng, 2014). Also, the model is more suitable for estimation since it is smooth (continuously differentiable) and has no explicit delay, which makes it more convenient for some optimization methods. The IDM+ offers more reasonable capacity values, and with no large acceleration differences from the IDM in most cases (except when the speed is much larger than the desired velocity and the spacing is much smaller than the desired spacing), (Schakel et al., 2010). The IDM+ achieves this by applying a minimization between the free flow term and the interaction term of the IDM. This makes the smooth topped equilibrium fundamental diagram of the IDM changed to a triangular shape. However, due to the minimum operator, the IDM+ is not continuous differentiable, which for our optimization method was not a problem. Equations 1 and 2 describe the IDM and the IDM+ models, respectively, with Equation 3 belonging to both the IDM and IDM+.

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

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

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

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

3.4.2. Estimation procedure and outcome

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

1. Definition of the IDM and IDM+ models
2. Identification of the input variables (speed, headway, etc.) (termed as state variables).
3. Identification of the output variable – in our case, it is acceleration of the ego vehicle.
4. Identification of the parameters to be estimated (v0 desired velocity, T safe time gap, s_0 jam spacing, alpha max acceleration, beta comfortable deceleration), along with their feasibility constraints (for example, the parameter must be non-zero)
5. Deciding on an initial set of parameters.
6. Using this initial set of parameters, along with the state variables of the vehicle in the current time step as input to the IDM and IDM+ models, calculation of the acceleration (output variable).
7. Using the calculated acceleration, updating the state variables of the vehicle at the next time step (new position, new speed, etc.).
8. Measuring the difference (error) between the calculated state variable and the actual state variable (from the data). The selected state variable is termed as Measure of Performance (MoP) and the error indicator Goodness of Fit (GoF).
9. Updating the initial parameter values with the intention to minimize the error.
10. Continuing steps 4-7, until satisfactory conditions are met.
11. Resulting in the final "best" set of parameter estimates.

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

The parameters estimation procedure was run on all driver-scenario combinations. In total, car-following parameters for 219 trajectories were estimated. Excluding the familiarization drive and the trajectories that had extremely large following time headway (greater than 10 seconds) and distance headway (greater than 300 meters) resulted in a final set of 173 trajectories with their estimated parameters. Figure 3.5 shows how these final trajectories were distributed between the 4 scenarios, the 4 orders, and the trails. Overall, there is a good balance between the scenarios and orders, therefore vastly reducing any bias in these variables.

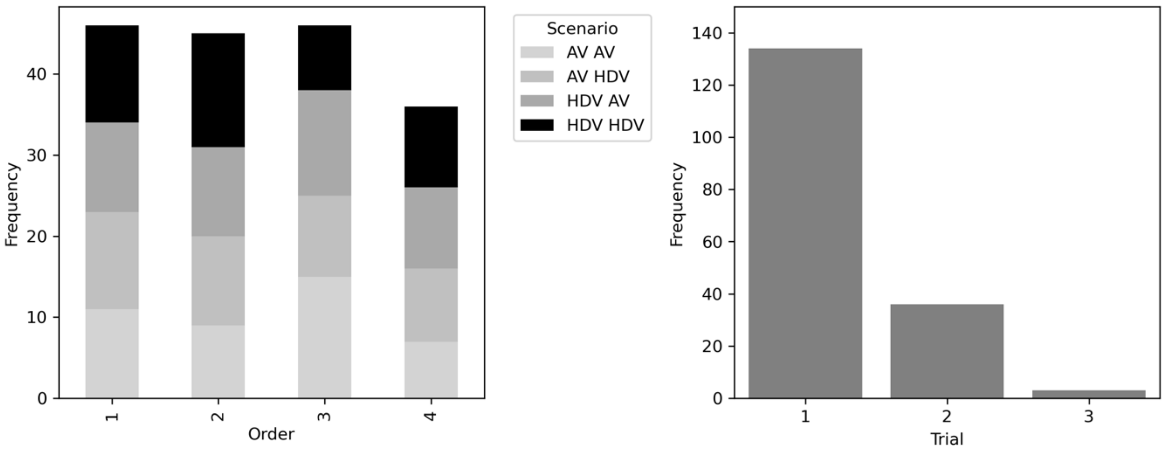
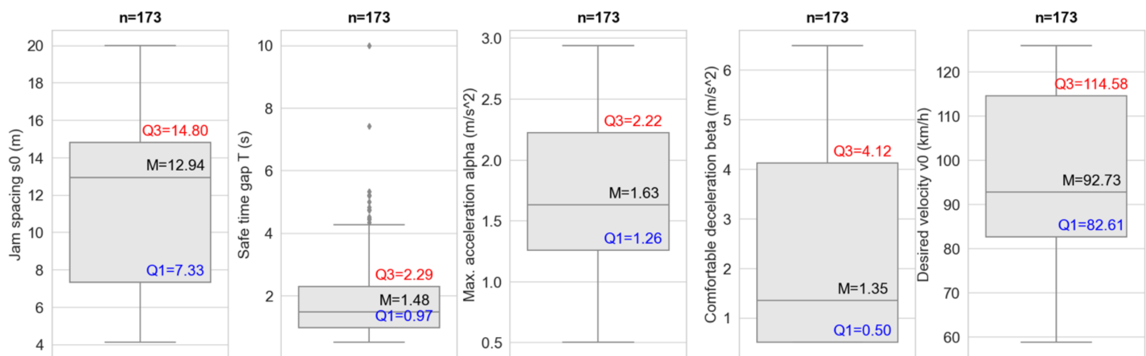


Figure 3.5: Distribution of final set of trajectories over the different scenarios, order, and trial. It shows the number of individual car-following trajectories in the final data used for modelling and analysis. (Scenarios coded as Appearance and Driving style)

Figure 3.6 shows the overall boxplot distributions of the parameters over all scenarios for the IDM (a), and for the IDM+ (b). The distributions between the two models look similar. Comparing the median values of IDM with that of IDM+ shows that for the IDM+, the safe time gap (T) is 0.5 s larger, the comfortable deceleration (beta) is 0.3 m/s2 smaller, the desired velocity (v0) is smaller by about 16 km/h, and the jam spacing (s0) and maximum acceleration (alpha) are very similar. Also, the inter-quartile range for the comfortable deceleration is larger for the IDM compared to the IDM+.



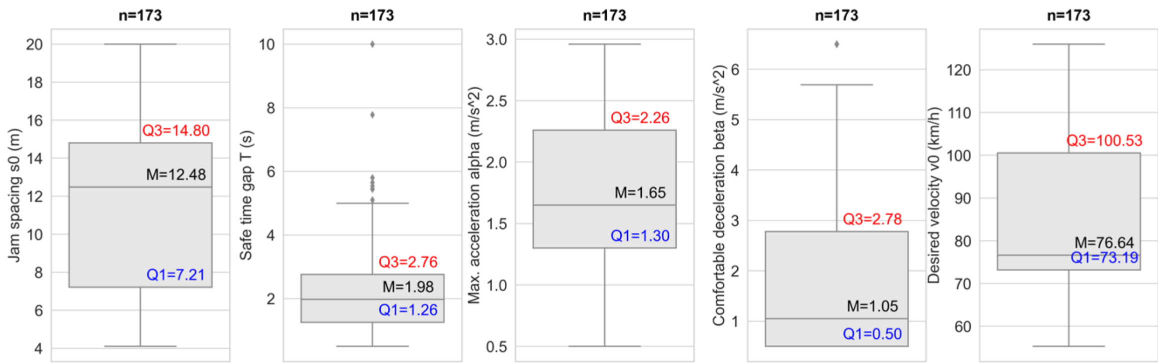


Figure 3.6: Boxplot distributions of the estimated parameters for the IDM (on previous page) and IDM+ (the above plot).

3.5. Estimated parameters

To help further interpret the results, these parameters were aggregated per scenario. Figure 3.7 and Figure 3.8 show boxplots of the parameter estimates, per scenario, for the IDM and IDM+ respectively. Certain differences can be observed. For instance, the jam spacing for the scenarios in which the lead vehicle is recognizable as AV, i.e., AV AV (AV Appearance, AV Driving style) and AV HDV (AV Appearance, HDV Driving style), seem smaller than the other two scenarios in which the lead vehicle is recognizable as HDV. Also, the safe time gap especially for AV AV scenario seems smaller. The median comfortable deceleration for the scenario AV HDV seems larger than the others. The largest visible changes are for the desired velocity, with the conventional traffic scenario HDV HDV having the largest median desired velocity, and the least median desired velocities are for the scenarios AV AV and AV HDV (in both scenarios, the vehicle is recognizable as AV). The changes in desired velocity medians are less noticeable in the IDM+ compared to the IDM.

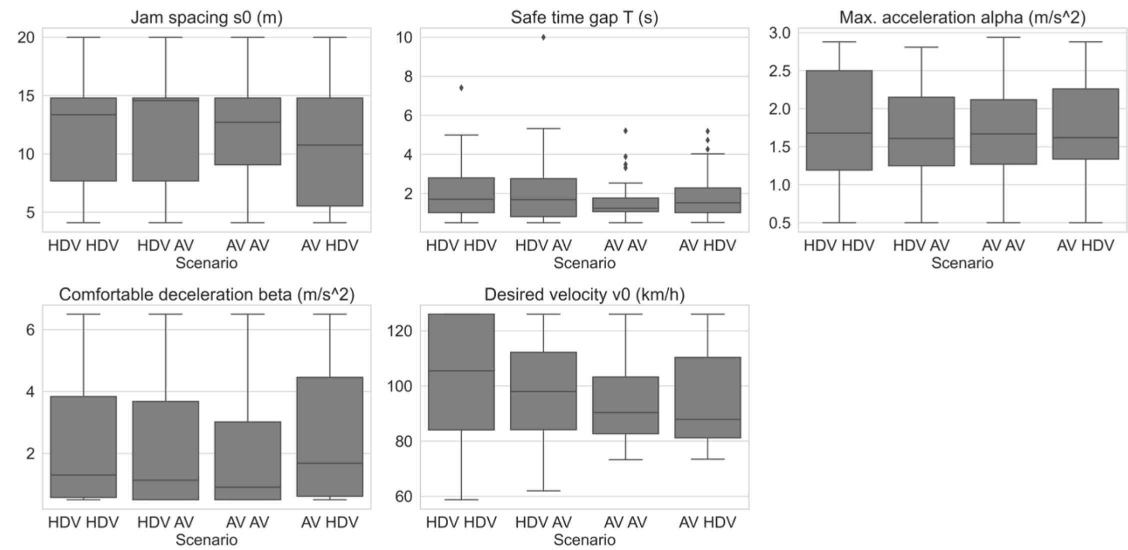


Figure 3.7: Boxplot distribution of the IDM parameters grouped by Scenario (Scenarios coded as Appearance and Driving style) .

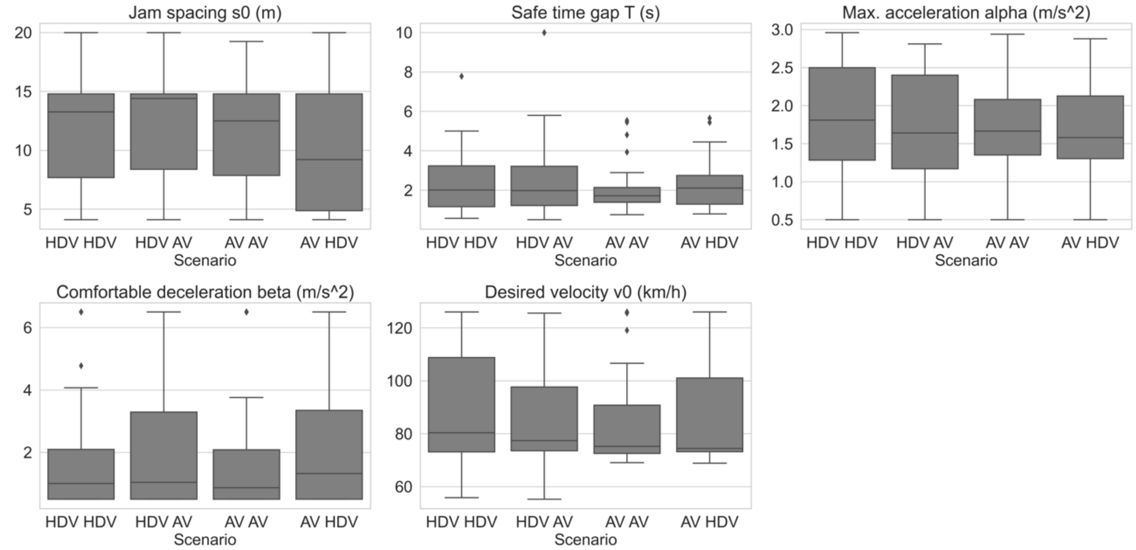


Figure 3.8: Boxplot distribution of the IDM+ parameters grouped by Scenario (Scenarios coded as Appearance and Driving style).

Table 3.2 and Table 3.3 present the median and standard deviation of the parameters for the different scenarios, and the differences from the base HDV-HDV scenario for the IDM and IDM+, respectively. What is notable is that the AV AV and AV HDV scenarios have the largest number of green shaded cells, indicating that the largest differences occurred in these scenarios where the AV was recognizable. This is noticeable for both the IDM and IDM+, but in particular for the IDM+. Additionally, the predominantly white cells in the Values column for AV AV show that except for median jam spacing, median max acceleration, and SD comfortable deceleration, the AV AV scenario had the smallest values for almost all parameters.

Table 3.2: Parameter estimates for IDM. Color shading is greyscale for the absolute “Values” per indicator (median and SD) between different scenarios. The other color shading is from green (max difference) to white (min difference) applicable for "Difference with HDV HDV" columns. (Scenarios coded as Appearance and Driving style)

Parameter	**Indicator**	**Values**				**Difference with HDV HDV**		
		HDV HDV	**HDV AV**	**AV AV**	**AV HDV**	**HDV AV**	**AV AV**	**AV HDV**
Jam spacing s0 (m)	Median	13,36	14,58	12,72	10,76	1.23	-0.64	-2.60
	SD	4,80	4,76	4,10	4,49	-0.03	-0.70	-0.31
Safe time gap T (s)	Median	1,70	1,68	1,25	1,52	-0.02	-0.45	-0.18
	SD	1,44	1,78	0,93	1,14	0.35	-0.51	-0.30
Max acceleration alpha (m/s2)	Median	1,68	1,61	1,67	1,62	-0.07	-0.01	-0.06
	SD	0,71	0,66	0,59	0,63	-0.05	-0.12	-0.08
Comfortable deceleration beta (m/s2)	Median	1,30	1,13	0,91	1,68	-0.17	-0.40	0.38
	SD	2,23	2,19	2,34	2,38	-0.04	0.11	0.15
Desired velocity v0 (km/h)	Median	105,45	97,96	90,43	87,82	-7.49	-15.02	-17.63
	SD	20,37	18,11	15,63	17,62	-2.26	-4.74	-2.75

Table 3.3: Parameter estimates for IDM+. Color shading is greyscale for the absolute "Values" per indicator (median and SD) between different scenarios. The other color shading is from green(max) to white(min) applicable for "Difference with HDV HDV" columns. (Scenarios coded as Appearance and Driving style)

Parameter	Indicator	Values				Difference with HDV HDV		
		HDV HDV	HDV AV	AV AV	AV HDV	HDV AV	AV AV	AV HDV
Jam spacing s0 (m)	Median	13,27	14,41	12,50	9,21	1.15	-0.77	-4.06
	SD	4,80	4,50	4,02	5,20	-0.30	-0.78	0.40
Safe time gap T (s)	Median	2,01	1,98	1,72	2,11	-0.03	-0.29	0.10
	SD	1,48	1,88	1,11	1,23	0.40	-0.38	-0.25
Max acceleration alpha (m/s2)	Median	1,81	1,64	1,67	1,58	-0.17	-0.15	-0.23
	SD	0,68	0,67	0,55	0,63	-0.01	-0.13	-0.06
Comfortable deceleration beta (m/s2)	Median	1,00	1,04	0,87	1,32	0.04	-0.13	0.32
	SD	1,96	2,30	2,07	2,24	0.34	0.11	0.29
Desired velocity v0 (km/h)	Median	80,38	77,40	75,28	74,45	-2.98	-5.10	-5.94
	SD	21,32	17,44	15,22	19,82	-3.88	-6.10	-1.50

To get a better insight regarding the differences between the IDM and IDM+, Table 3.4 presents the IDM and IDM+ car-following model parameters and their values for the different scenarios. Also, the third column for each scenario shows the differences in parameters values between the IDM and IDM+. Additionally, the RMSE, which is the goodness of fit indicator is also reported for all the scenarios for the two models. The columns indicating the differences are shaded from green (greatest positive difference) to red (greatest negative difference). Overall, there are some differences that are notable. The median desired velocity has the greatest differences, with the IDM+ having in general smaller desired velocities compared to the IDM for all scenarios. Also, the median time headway is greater for the IDM+ compared to the IDM, for all scenarios. As for goodness of fit (RMSE), both models have similar values in general for all scenarios. The RMSE for both models is presented in the form of boxplot distribution in Figure 3.9, which shows the similarity. Given that the actual spacing had a Mean of 56.5 m and SD 41.1 m, the RMSEs are generally around 25% of the mean spacing, which is reasonably good and also similar to previous estimations using genetic algorithm for the IDM (Kesting & Treiber, 2008).

Table 3.4: Comparing estimates and goodness of fit of IDM and IDM+ (Diff relate to the difference in estimates between IDM and IDM+) (Scenarios coded as Appearance and Driving style)

		HDV HDV			HDV AV			AV AV			AV HDV		
Parameter		**IDM**	**IDM+**	**Diff**	**IDM**	**IDM+**	**Diff**	**IDM**	**IDM+**	**Diff**	**IDM**	**IDM+**	**Diff**
s0	**Median**	13,36	13,27	-0,09	14,58	14,41	-0,17	12,72	12,50	-0,22	10,76	9,21	-1,55
	SD	4,80	4,80	0,00	4,76	4,50	-0,26	4,10	4,02	-0,08	4,49	5,20	0,71
T	**Median**	1,70	2,01	0,32	1,68	1,98	0,30	1,25	1,72	0,48	1,52	2,11	0,59
	SD	1,44	1,48	0,04	1,78	1,88	0,10	0,93	1,11	0,18	1,14	1,23	0,09
alpha	**Median**	1,68	1,81	0,13	1,61	1,64	0,03	1,67	1,67	0,00	1,62	1,58	-0,04
	SD	0,71	0,68	-0,02	0,66	0,67	0,02	0,59	0,55	-0,04	0,63	0,63	0,00
beta	**Median**	1,30	1,00	-0,30	1,13	1,04	-0,09	0,91	0,87	-0,04	1,68	1,32	-0,36
	SD	2,23	1,96	-0,28	2,19	2,30	0,11	2,34	2,07	-0,27	2,38	2,24	-0,14
v0	**Median**	105,45	80,38	-25,07	97,96	77,40	-20,56	90,43	75,28	-15,15	87,82	74,45	-13,38
	SD	20,37	21,32	0,95	18,11	17,44	-0,67	15,63	15,22	-0,41	17,62	19,82	2,20
RMSE	**Mean**	12,91	12,70	-0,21	16,37	15,99	-0,38	13,83	13,92	0,09	14,02	13,60	-0,42
	SD	9,12	9,08	-0,04	22,48	19,3	-3,18	6,58	6,96	0,38	9,31	7,95	-1,36

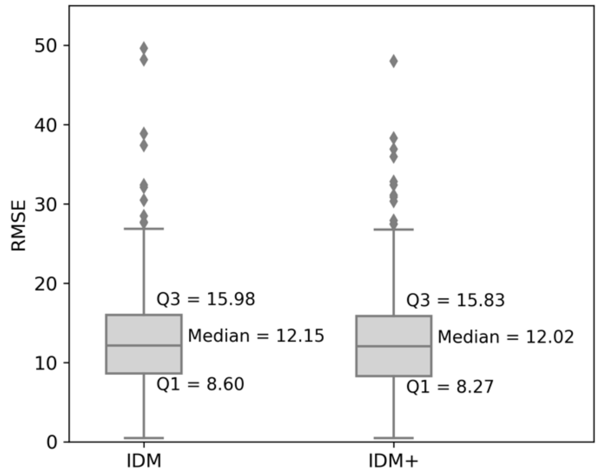


Figure 3.9: Boxplots for RMSE of parameters estimation using IDM and IDM+.

3.6. Regression modelling of parameters

The estimation process resulted in a unique set of parameters for every driver-scenario-trial combination. Our goal is to understand the effect of mixed traffic on the parameters of the IDM and IDM+, and hence on the car-following behavior. We estimated 5 univariate linear mixed models that can handle random effects (in this case, random effect parameter for the intercept). We adopted a linear mixed model for each of the 5 parameter estimates, because all the 5 parameters are continuous variables. The dependent variables are the 5 parameters: s0 (jam spacing), T (safe time gap), alpha (maximum acceleration), beta (comfortable deceleration), and v0 (desired velocity). The independent variables were the scenario related variables which included the AV appearance and AV driving style. In addition, the demographic variables and driving styles were considered. The variables “Trial”, “Years Driving NL”, “Education Level”, and “Employment status” were excluded due to relatively low variation in the dataset. The remaining demographic variables were tested for multicollinearity. Figure 3.10 shows the correlation matrix between the demographic variables and the Pearson correlation coefficients, with only the statistically significant correlations cells being highlighted (p-value less than 0.05). If two variables were significantly and highly correlated, the one having a larger number of other correlated variables was removed. Based on this, the following variables were excluded: “Knowledge AVs”, “Driving comfort NL”, “Anxious”, “Dissociative and Distress-reducing”.

	Driving Comfort NL	Trust Tech	Trust AVs	Knowledge AV	Experience AV	Anxious	Dissociative and Distress-reducing	Angry and Hostile	Patient and Careful
Driving Comfort NL	1,00								
Trust Tech		1,00							
Trust AVs		0,55	1,00						
Knowledge AV	0,45			1,00					
Experience AV	0,34			0,59	1,00				
Anxious	0,19		0,23	0,50	0,35	1,00			
Dissociative and Distress-reducing	-0,25	0,44	0,45			0,33	1,00		
Angry and Hostile	0,23			0,17	0,23	0,63	0,31	1,00	
Patient and Careful		0,61	0,49	0,18		0,18	0,48	0,22	1,00

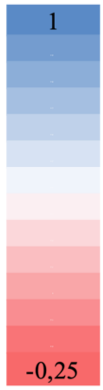


Figure 3.10: Correlation matrix between continuous demographic variables (only significant correlations displayed with the Pearson correlation coefficients)

The variables that were kept were: "Gender", "Age Group", "Angry and Hostile", "Patient and Careful", "Trust_Tech", "Trust AVs", "Experience AV", "AV appearance", "AV driving style", "Order of Scenario". The "Participant number" was also kept. After this, correlations with categorical variables were also tested. Table 3.5 presents the results. All were not significant, so all these variables were kept.

Table 3.5: Correlations of categorical variables (all not statistically significant)

Variable 1	Variable 2	Test type	Result
Age Group	Gender	Chi-squared	Chi2 = 1.15, p-value = 0.56
Age Group	AV appearance	Chi-squared	Chi2 = 1.17, p-value = 0.56
Age Group	AV driving style	Chi-squared	Chi2 = 0.44, p-value = 0.8
Gender	AV appearance	Chi-squared	Chi2 = 0.03, p-value = 0.86
Gender	AV driving style	Chi-squared	Chi2 = 0.05, p-value = 0.83
Age Group	Trust Tech	Kruskal Wallis	H-statistic: 0.07, p-value: 0.96
Age Group	Angry and Hostile	Kruskal Wallis	H-statistic: 0.57, p-value: 0.75
Age Group	Patient and Careful	Kruskal Wallis	H-statistic: 5.0, p-value: 0.08
Gender	Trust Tech	Kruskal Wallis	H-statistic: 1.71, p-value: 0.19
Gender	Angry and Hostile	Kruskal Wallis	H-statistic: 4.27, p-value: 0.04
Gender	Patient and Careful	Kruskal Wallis	H-statistic: 0.14, p-value: 0.71

With the remaining variables, univariate linear mixed models were estimated. First, the categorical variables were dummy coded appropriately. Univariate linear mixed effects models were estimated for s0, T, alpha, beta, and v0. Participants number was used as random intercept to account for repeated measures for every participant. The best model was selected based on the combination of the following criteria: theoretical domain knowledge, importance of the variable, the significance (p-values) of the estimates, and the Akaike Information Criteria (AIC). We added back Trust_AVs as it was relevant even though it had a correlation with Trust_Tech and tested for different model options. Even though the multicollinearity test using the Variance Inflation Factor (VIF) found that it was okay to have both variables in the model, the Condition Index (CI) showed there were multicollinearity problems. Hence, we decided to only keep Trust_AVs as this is the main variable of interest (the model performed almost the same as the one that had only Trust_Tech). Table 3.6 and Table 3.7 present the coefficient estimates for the 5 parameters, using IDM and IDM+ respectively.

Table 3.6: Coefficient estimates for IDM based univariate linear mixed models for the 5 parameters (p-values in brackets). DS – driving style, App –- Appearance

	Jam spacing s0 (m)	Safe time gap T (s)	Max accel. alpha (m/s2)	Comfortable deceleration beta (m/s2)	Desired velocity v0 (km/h)
Intercept	7,35 (0,22)	-0,68 (0,73)	2,21 (0,02) *	0,38 (0,9)	107,51 (<0,01)**
Gender: Female	1,12 (0,26)	0,58 (0,08) .	0,02 (0,92)	0,01 (0,98)	-2,71 (0,53)
Age: Middle aged 45 to 65	0,83 (0,49)	0,12 (0,76)	-0,16 (0,38)	0,01 (0,99)	-2,98 (0,57)
Age: Older 70+	4,1 (<0,01)**	0,87 (0,03) *	0,18 (0,34)	-0,88 (0,15)	-11,5 (0,03) *
Driver DS: Angry and Hostile	-0,91 (0,24)	-0,31 (0,22)	-0,09 (0,47)	0,55 (0,16)	-0,86 (0,8)
Driver DS: Patient and Careful	1,13 (0,29)	0,53 (0,13)	-0,06 (0,74)	0,29 (0,58)	0,53 (0,91)
Trust in AVs	0,07 (0,95)	-0,54 (0,12)	0,13 (0,43)	-0,88 (0,13)	4,74 (0,32)
Vehicle App: AV	-1,34 (0,05) *	-0,06 (0,79)	-0,02 (0,83)	0,23 (0,58)	-6,36 (0,04) *
Vehicle DS: AV	-0,35 (0,6)	0,06 (0,76)	-0,14 (0,2)	0,15 (0,71)	-3,75 (0,22)
Order: 2	-2,12 (<0,01)**	0,08 (0,71)	0,05 (0,67)	-0,46 (0,26)	2,34 (0,44)
Order: 3	-0,72 (0,26)	0 (0,99)	-0,19 (0,07) .	-0,22 (0,58)	-1,61 (0,59)
Order: 4	-2,4 (<0,01)**	0,08 (0,73)	0,06 (0,6)	-0,81 (0,07) .	-4,26 (0,2)
Trust in AVs * Vehicle App: AV	-1,69 (0,05) .	0,01 (0,98)	-0,06 (0,68)	1,01 (0,06) .	-4,13 (0,3)
Trust in AVs * Vehicle DS: AV	-0,69 (0,42)	0,16 (0,56)	0,12 (0,39)	-0,24 (0,65)	-2,97 (0,45)
Vehicle App: AV * Vehicle DS: AV	1,35 (0,15)	-0,33 (0,27)	0,1 (0,51)	-0,47 (0,43)	1,72 (0,69)
Group variance for Participant ID: Intercept (Residual)	2,71 (2,99)	0,9 (0,94)	0,42 (0,49)	1,2 (1,9)	11,48 (14)
AIC	919,45	564,79	356,66	759,45	1392,07
Log-likelihood	-442,72	-265,39	-161,33	-362,72	-679,04

. <0.1 * < 0.05 ** < 0.01

Table 3.6 and 3.7 reveal some significant parameters, at significance levels <0.1, <0.05, and <0.01. The AV appearance was found to reduce jam spacing and desired velocity. The interaction term with trust in AVs showed that when drivers have higher levels of trust in AVs, an AV appearance further reduced the jam spacing. Additionally, when the trust in AVs was higher, an AV appearance also resulted in larger comfortable deceleration. As for personal characteristics, older drivers tended to have larger jam spacing, larger safe time gap, and smaller desired speeds compared to younger drivers. Female drivers had larger safe time gaps than male drivers. As for driving style, drivers with greater inclination to patient and careful driving styles had larger safe time gaps. Finally, the group variance for Participant ID is significant, showing that significant differences were observed between participants at the level of the subjects, which the mixed model correctly considered. The order of the scenarios also played a role. Scenarios with Order 2 shows smaller jam spacing compared to Order 1. Scenarios with Order 3 saw smaller max acceleration, and scenarios with Order 4 saw smaller jam spacing and smaller comfortable deceleration compared to Order 1. In the next section, we discuss the main implications from all these results.

Table 3.7: Coefficient estimates for IDM+ based univariate linear mixed models for the 5 parameters (p-values in brackets). DS – driving style, App — Appearance

	Jam spacing s0 (m)	**Safe time gap T (s)**	**Max accel. alpha (m/s2)**	**Comfortable deceleration beta (m/s2)**	**Desired velocity v0 (km/h)**
Intercept	9,28 (0,13)	-1,48 (0,47)	2,39 (<0,01)**	-1,05 (0,68)	94,65 (<0,01)**
Gender: Female	0,97 (0,34)	0,68 (0,05) *	-0,07 (0,62)	-0,17 (0,68)	-0,67 (0,87)
Age: Middle aged 45 to 65	0,85 (0,49)	0,28 (0,49)	-0,1 (0,55)	0,44 (0,38)	-0,89 (0,86)
Age: Older 70+	3,67 (<0,01)**	1,11 (<0,01)**	0,2 (0,26)	-0,3 (0,56)	-9,71 (0,06) .
Driver DS: Angry and Hostile	-0,91 (0,25)	-0,21 (0,42)	-0,06 (0,59)	0,44 (0,19)	2,85 (0,38)
Driver DS: Patient and Careful	0,79 (0,47)	0,7 (0,06) .	-0,09 (0,56)	0,49 (0,28)	-1,43 (0,75)
Trust in AVs	0,22 (0,84)	-0,6 (0,1)	0,01 (0,93)	-0,56 (0,29)	3,94 (0,4)
Vehicle App: AV	-1,56 (0,03) *	0,1 (0,66)	-0,09 (0,46)	0,37 (0,39)	-1,55 (0,64)
Vehicle DS: AV	-0,24 (0,73)	0,08 (0,72)	-0,08 (0,48)	0,57 (0,18)	-3,66 (0,27)
Order: 2	-2,5 (<0,01)**	0,06 (0,77)	0 (0,98)	-0,46 (0,28)	4,59 (0,16)
Order: 3	-0,85 (0,21)	-0,18 (0,4)	-0,19 (0,1) .	-0,24 (0,56)	-4,13 (0,2)
Order: 4	-2,82 (<0,01)**	0,04 (0,87)	0,07 (0,59)	-1,04 (0,02) *	0,29 (0,93)
Trust in AVs * Vehicle App: AV	-1,25 (0,17)	0,09 (0,77)	0,04 (0,8)	0,7 (0,21)	-1,16 (0,79)
Trust in AVs * Vehicle DS: AV	-1,37 (0,12)	0,13 (0,65)	0,09 (0,55)	-0,53 (0,34)	-7,15 (0,09) .
Vehicle App: AV * Vehicle DS: AV	1,45 (0,14)	-0,4 (0,22)	0,08 (0,6)	-0,98 (0,11)	-1,62 (0,73)
Group variance for Participant ID: Intercept (Residual)	2,74 (3,13)	0,91 (1,03)	0,36 (0,53)	0,84 (1,95)	10,39 (15,03)
AIC	931,35	588,04	365,27	752,45	1405,21
Log-likelihood	-448,67	-277,02	-165,63	-359,23	-685,61

. <0.1   * < 0.05   ** < 0.01

3.7. Discussion and Limitations

In this section, we discuss the results in line with the research questions that were defined and the literature. Later, we discuss some key limitations to this research.

1. **How can car-following model parameters capture the changes that occur in the behavior of HDVs in mixed traffic?**

We attempted to capture HDV car-following behavior in mixed traffic using car-following models. We selected two models, the IDM and the IDM+, and estimated them for different mixed traffic conditions: AVs non-recognizable and driving like HDVs (Scenario code HDV HDV), AVs non-recognizable and driving differently from HDVs (Scenario code HDV AV), AVs recognizable and driving differently from HDVs (Scenario code AV AV), and AVs recognizable and driving like HDVs (Scenario code AV HDV). We presented the median and standard deviation values of the parameters for the different scenarios for both models. These parameters collectively describe the nature of car-following in mixed traffic conditions. Moreover, future studies wanting to implement the IDM or IDM+ models for such mixed traffic conditions can use these parameter estimates to model HDV driving behavior in mixed traffic. It is important to use models that are estimated for mixed traffic because they capture the effects of mixed traffic-specific factors such as Vehicle appearance (AV or HDV), Vehicle driving style

(AV or HDV), and trust in AVs, among other factors. These AV-specific factors, turning out to have statistically significant effects on the model parameters justify the necessity of using mixed traffic specific models.

While this study used two existing models (IDM and IDM+), it is also important to consider the necessity and possibility of designing models specific for mixed traffic conditions. Such models could have a totally different mechanism altogether, as opposed to estimating a new set of parameters as what we did in this study.

2. **How does the choice of the car-following model affect the measured impact of mixed traffic on HDV car-following behavior?**

There are many popular models available to describe car-following behavior. Through this research question, we wanted to explore the implication of selecting a specific car-following model over another model. In our study, we selected the IDM and IDM+. Both models having the same parameters, it helps to observe the differences between the parameters between the two models thus helping to understand the implications of model formulation. We presented the differences in the estimates between the IDM and IDM+ for each scenario, in addition to the parameter estimates. Differences were mainly observed for the parameters safe time gap and desired velocity. Compared to that for the IDM, the median safe time gap for the IDM+ was larger by 0.31 seconds for the scenario HDV HDV, by 0.30 seconds for the scenario HDV AV, by 0.47 seconds for the scenario AV AV, and by 0.59 seconds for the scenario AV HDV. Compared to that for the IDM, the median desired velocity for the IDM+ was smaller by 25.07 km/h for the scenario HDV HDV, by 20.56 km/h for the scenario HDV AV, by 15.15 km/h for the scenario AV AV, and by 13.38 km/h for the scenario AV HDV. The goodness of fit (RMSE) was mostly the same between the IDM and IDM+.

Therefore, the choice of the model type affects how the HDV behavior in mixed traffic is modelled, and thereby resulting in implications on the impacts (on traffic flow or safety) that could later be measured through simulations. For example, to study a scenario where AV are recognizable and have an AV-like driving style (scenario AV AV), choosing the IDM+ instead of IDM would mean simulating HDVs that drive having about 15 km/h lower desired velocities, with about 0.5 seconds larger safe time gaps. So, it is important to be careful in the choice of the models. A nuance must be made here on the reason why the two models provide different desired velocity values. This has to do with how the desired velocity parameter plays a role in the calibration of the models. The IDM+ has a constraint that puts a limit on acceleration, which makes it more conservative than the IDM. The IDM, not having this constraint, can produce higher desired velocities. Therefore, the desired velocity parameter should not be strictly viewed as representing the true velocity at which drivers would like to drive at free-flow, but more as a parameter that compensates for the errors or artefacts in the model. Hence, the parameters should not be taken out separately and applied as they are defined, but they should be used together with the model context where they belong.

3. **What is the effect of mixed traffic on car-following behavior of HDVs?**

To understand the effects of mixed traffic factors on the car-following behavior of HDVs, we estimated univariate linear mixed regression models for the parameters of the IDM and IDM+. This provided insight into the precise magnitude and direction of the effects of mixed traffic factors on each of the car-following parameters. We estimated the parameters of the IDM and IDM+ models separately. Generally, the effects of the various considered factors are similar for both models, with statistically significant effects seen for all parameters. We combine the insights from both models to understand the impacts of the various mixed traffic factors on the car-following model parameters. We also discuss the impact of the drivers' personal characteristics on these parameters, along with the effect of scenario order.

Three factors are attributed to mixed traffic conditions, namely, the Vehicle appearance (AV or HDV), the Vehicle driving style (AV or HDV), and trust in AVs. Significant effects were observed for these factors on jam spacing, comfortable deceleration, and the desired speed. When the AV was recognizable as AV (appearance AV), then the participants maintained smaller jam spacing (smaller by around 1.5 m) compared to the scenarios in which the lead vehicle was recognizable as HDV. This means that drivers are comfortable keeping a closer distance to the AV compared to the HDV when at standstill, suggesting higher trust in AVs (the safe time gap was also smaller when AV was recognizable). Also, in the safe time gap parameter estimates, we found that for the IDM, the safe time gap estimates were smaller for scenarios where the AV was recognizable. This is also seen in previous literature (Wen et al., 2022; Zhao et al., 2020). For example, Zhao et al. (2020) also found that those who trust AVs more maintain a shorter following distance with the AV leader. The fact that drivers keep a closer distance due to higher trust, is supported by the observation that when the trust in AVs was higher, the jam spacing further reduced (by around 2 m). While AV appearance reduced the jam spacing, it also reduced the desired velocity (by approx. 6 km/h). This finding is interesting as higher trust would mean drivers would drive faster when following a lead vehicle. However, this is not the case because in the experiment, drivers were constrained by the lead vehicle and could not overtake. Therefore, it is possible that drivers thought AVs had a more conservative driving style (which they did when they followed AV driving style). Drivers having greater trust in AVs also had further smaller desired velocity (by approx. 7 km/h) when the vehicle had an AV driving style (more conservative). These findings are consistent in supporting the explanation that drivers perceived AVs as safe and conservative. Therefore, they were more comfortable to keep a close distance (indicated by smaller standstill distance) but when constrained (due to lack of opportunity for overtaking), they had smaller desired velocities. Another finding was that when trust in AVs was higher, it resulted in a larger comfortable deceleration when the vehicle had AV appearance (by about 1 m/s2). This suggests that drivers had higher braking magnitudes when following an AV appearing vehicle than when following an HDV appearing vehicle. This result is in line with the smaller jam distance, as if drivers follow AVs closer, then it is likely that they brake harder. This also points to some traffic safety implications. A connection can be made with the study on real-world crashes between AVs and HDVs which found that most crashes occur when HDV is following an AV that comes to a stop (Xu et al., 2019). Finally, it is also important to notice that mixed traffic factors had no effect on the safe time gap, which was mainly influenced by the personal characteristics. However, the distribution of safe time gap in Figure 3.7 and Figure 3.8 suggest that the safe time gap was smallest for the scenario App AV DS AV. This was not reflected however in the model. A nuance on desired velocity is also of relevance here. For the same model, there were differences observed in desired velocity parameter between the scenarios. This could ap pear unnatural as a driver's desired velocity when in free flow should be independent of the type of vehicle driving in front. Still, we found differences. This suggests that drivers may, at least, temporarily, have different desired velocities as a consequence of how they perceive the lead vehicle. This could be similar to the effect that drivers may wish to drive at higher than their normal speeds when following a slow moving car.

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

While the above results and discussion is in light of the model results, it must not be taken directly that the factors having statistically insignificant effects will have no effects on driving behavior. It is certain that with further research and more data, deeper insights into their effects can be gained. For example, it may be that the model shows that vehicle appearance has a significant effect on desired velocity. However, it is still possible this also results in a change in safe time gap, which is not captured in the model. But the differences in these parameters can be observed in the descriptive overview across the scenarios. For example, the safe time gap in comparison to the HDV HDV scenario, was: 0.45 seconds smaller for the AV AV scenario, 0.18 seconds smaller for the AV HDV scenario, and almost equal to the HDV AV scenario. Therefore, the AV being recognizable resulted in a reduction of the safe time gaps. This of course, needs to be statistically tested with future research.

3.8. Limitations

Firstly, we conducted one driving simulator experiment in which participants drove four different scenarios. While this provides useful insights into the drivers' behavior in mixed traffic, it leaves an open question of whether the observed behavior remains unchanged over time. For this, a longer-term study is needed. Secondly, we used only two models, the IDM and IDM+. While this allowed a comparison of similar but specifically different models, we did not compare other models that have a different mechanism altogether (such as the Gipps model or the psychophysical model). Thirdly, in the car-following section, drivers drove based on the experience /expectations they had gained from driving in mixed traffic in the prior route. Therefore, the car-following section measured what could be termed as the behavior based on learning or developed expectations. It is possible that drivers could behave differently if they had closer and longer interactions with AVs specifically and could observe the way the AV was following its leader in the car-following section. Fourth, all observed behavior depends on the set up of the experiment. Particularly, the way we defined AV driving behavior would directly affect how participants perceive and interact with the AVs. In real life however, AVs have different driving styles which are also different between different manufacturers. Finally, general limitations applicable to driving simulator studies concerning their realism and validity also apply to the results of this research.

3.9. Potential Applications & Recommendations

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

3.9.1. Potential applications

Researchers can use the results of this study that show how various factors affect HDVs' car-following behavior. These factors include both the mixed traffic related factors as well as the demographic and driving styles factors. Such insights can help researchers to incorporate (or exclude) these factors in their studies. The estimated parameters of the IDM and IDM+ for different mixed traffic conditions can be directly implemented for modelling car-following behavior in various types of studies. For instance, they can be implemented in simulation studies focusing on mixed traffic to gain insights into the implications on traffic safety and efficiency.

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

Vehicle manufacturers can use the results of this study in the design and development of their AVs in two ways. First, they can make better informed decisions on aspects such as the appearance and driving style of their AVs, by understanding the potential impacts on HDVs. Second, they can use the HDV car-following models in the training of AV driving behavior, depending on their goals.

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

3.9.2. Recommendations for future research

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

3.10. References

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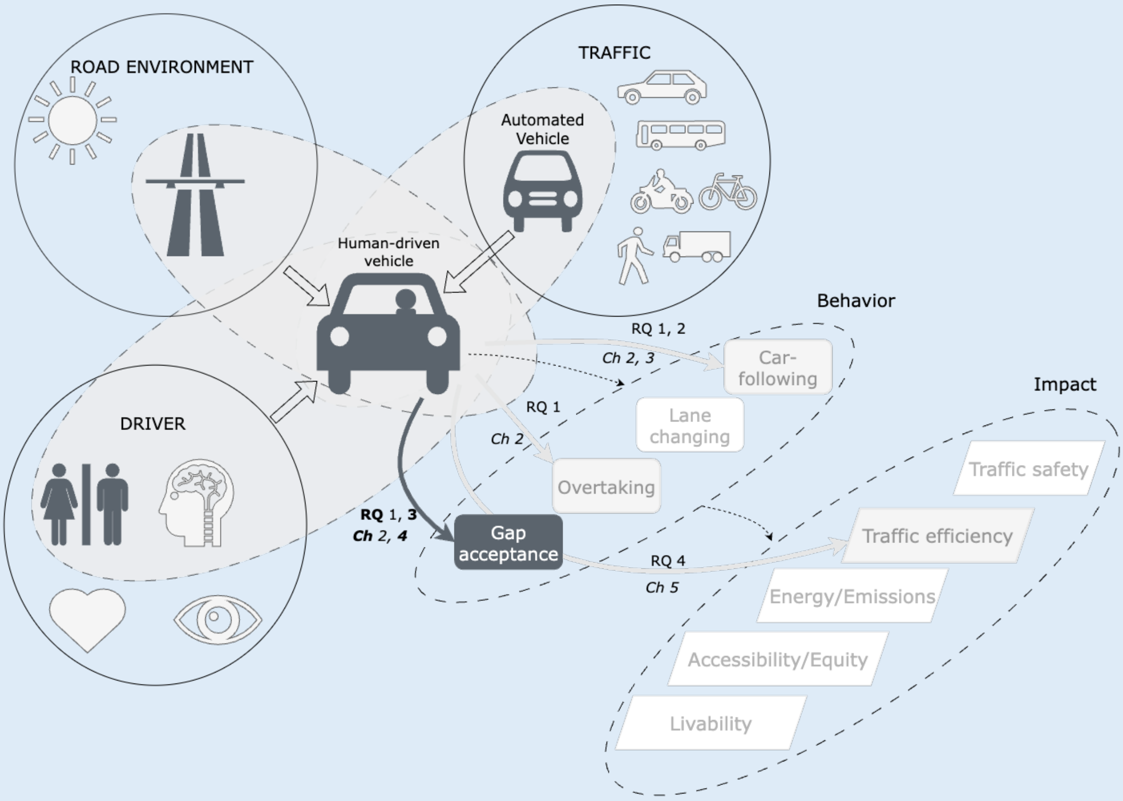
Chapter 4:

Investigating gap-acceptance behavior: A driving simulator experiment

Chapter 3 investigated car following behavior. In Chapter 4, we focus on gap acceptance behavior at priority-T intersections. In a driving simulator experiment, drivers were asked to enter a major road from a minor road, which involved waiting for an acceptable gap on the major road traffic. We performed descriptive analyses to study the effect of AV recognizability and AV driving style on human drivers' gap acceptance behavior.



Highlights

- Human drivers' gap acceptance behavior was studied in a driving simulator.
- Traffic included human driven vehicles and automated vehicles (AVs)
- Recognizable and aggressive AVs resulted in larger accepted and critical gaps.
- Non-recognizable and aggressive AVs resulted in smaller critical gaps.
- Results suggest that AVs' appearance and driving styles affect human driving behavior during gap acceptance.

This chapter is based on the publication: Reddy, N., Hoogendoorn, S. P., & Farah, H. (2022). *How do the recognizability and driving styles of automated vehicles affect human drivers' gap acceptance at T- Intersections?* Transportation Research Part F: Traffic Psychology and Behaviour, 90, 451–465. https://doi.org/10.1016/J.TRF.2022.09.018

Chapter 4
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4. Investigating gap-acceptance behavior: A driving simulator experiment

4.1. Introduction

The introduction of Automated Vehicles (AVs) on public roads has been fueled by expected positive impacts on traffic safety, reduction in traffic congestion, and lower environmental impacts (Greenblatt & Shaheen, 2015; Piao et al., 2016). One probable scenario is that AVs are deployed on the existing infrastructure, therefore driving alongside Human Driven Vehicles (HDVs). Such a "mixed" traffic environment consisting of both HDVs and AVs could result in interactions of a different nature. This would especially be noticeable in critical scenarios such as discontinuities (e.g., intersections, weaving sections, on-ramps, and off-ramps) and may positively or negatively affect traffic flow operations and safety. Therefore, road authorities and policymakers desire to predict the potential consequences of mixed traffic to take appropriate measures that not only minimize and possibly prevent negative and dangerous effects but also that may drive positive effects. For this, an in-depth understanding of how human drivers might adapt and change their behavior when interacting with AVs compared to when interacting with other HDVs is needed.

Existing studies that aim to predict the traffic flow operations and traffic safety in mixed traffic generally model human driving using models that are developed for 100% human-driven traffic (Papadoulis et al., 2019; Yao et al., 2020; Ye & Yamamoto, 2018). Recent studies, which are later discussed, including field test experiments, have shown that human drivers adapt their driving behavior in the presence of AVs. Behavioral adaptation is defined 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" (Kulmala & Rama, 2013). While studies have looked at behavioral adaptation in mixed traffic, the focus has primarily been on car-following and lane-changing behavior on straight road sections, while limited attention has been given to discontinuities. A crucial behavior for traffic safety and efficiency at priority T-intersections is gap acceptance of a vehicle on a minor road (approach) that wishes to merge onto a major road. Priority intersections are a critical part of the road network that affect the network's traffic efficiency and safety (29% of road deaths in the Netherlands occurred at intersections (Road Deaths in the Netherlands. SWOV Factsheet, 2022). At a priority T-intersection, the minor road vehicle generally comes to a complete stop or slows down (before a Stop sign or a Give-Way sign, respectively) and waits until it finds an appropriate gap in the major road traffic stream.

Gap acceptance behavior at priority-controlled intersections in conventional traffic conditions has been extensively studied in the literature. These studies have focused on observing rejected gaps, observing and modeling accepted gaps (Beanland et al., 2013; Yan et al., 2007), estimating critical gaps, and modeling critical gaps (Gattis & Low, 1999; Guo & Lin, 2011; Pollatschek et al., 2002; Rossi et al., 2020). The size of the gaps offered was found to be the most influencing factor in gap acceptance behavior (Beanland et al., 2013). Most existing studies on gap acceptance at priority intersections have looked at conventional traffic conditions. A limited number of studies have investigated the potential behavioral adaptation of human drivers' gap acceptance at unsignalized intersections when interacting with AVs. (Trende et al., 2019) used a driving simulator to compare the gap acceptance of drivers at priority intersections in front of HDVs and front of AVs. Drivers more frequently accepted gaps in front of AVs (drivers were informed that AVs avoided collisions), although all cars drove similarly. (Soni, 2020) studied similar gap acceptance behavior in a controlled field test using the Wizard of Oz method. Drivers were found to have significantly lower critical gaps when merging in front of AVs compared to HDVs, which further reduced when positive information about AVs was provided. Most other studies focused on investigating drivers' potential behavioral adaptation when interacting with AVs in car-following behaviors, and few on lane-changing behavior. Considering the limited studies on gap acceptance, insights from the studies on car-following and lane-changing behavior are summarized below as these can still be useful and relevant for the current study.

Lee et al. (2018) studied human drivers' lane-changing in an AV platoon environment using a driving simulator. They found that human drivers drove more radically as indicated by greater steering magnitude and steering velocity during lane-changing. Duration of lane change preparation tended to increase with increasing AV penetration rate. For example, an increase in AV penetration rate from 0% to 50% led to a 60% increase in lane change preparation duration. Moreover, females and older drivers were less likely to successfully change lanes in general across the different penetration rates. Other studies (Fuest et al., 2020; Gouy et al., 2014; Rahmati et al., 2019; Razmi Rad et al., 2021; Schoenmakers et al., 2021; Stange et al., 2022; Zhao et al., 2020) have looked at such behavioral adaptation of human drivers (mainly car-following and lane-changing behaviors) in mixed traffic considering recognizability and driving style of AVs. Gouy et al. (2014) studied the car-following behavior of HDVs when driving next to AV platoons using a driving simulator. They found that drivers adopted smaller average and minimum time headways, and kept a time headway below a threshold of 1s for a longer duration when driving next to platoons of AVs that maintained time headways of 0.3 s compared to platoons that maintained time headways of 1.4 s. Zhao et al. (2020) conducted a field experiment to study HDVs' car-following behavior when following an AV considering its recognizability. When AV was recognizable, AV-believers maintained smaller time headways, AV skeptics maintained larger time headways. When the AV was not recognizable, no difference in behavior was found. Rahmati et al. (2019) also conducted a field experiment to study HDVs' car-following behavior when following a vehicle that drove like an HDV, and also when following a vehicle that drove like an AV (according to a predefined model). When following the AV-like driving vehicle, drivers maintained smoother speed profiles, maintained a smaller gap with the AV, and drove with less abrupt accelerations and decelerations, as compared to when following the HDV-like driving vehicle. Zhong et al. (2019) adopted microsimulation to study the effect of two CACC driving strategies (ad-hoc coordination, and local coordination) on human-driven vehicles, as well as throughput (vehicles per hour) and productivity (ratio of vehicle miles traveled to vehicle hours traveled) of a highway segment. In general, they observed an increase in throughput and productivity with an increasing penetration rate of AVs. The lane change frequency of human-driven vehicles decreased with the increasing penetration rate of AVs. Additionally, the distribution of hard braking observations for human-driven vehicles between the two CACC coordination strategies was significantly different when HDVs follow the AVs but not different when HDVs follow other HDVs.

Razmi Rad et al. (2021) studied HDV car-following and lane-changing behavior in a driving simulator study when driving next to a dedicated lane for AVs and compared that to a mixed traffic situation with no dedicated lanes. The authors found that HDVs adopted shorter time headways with the leader when driving on the lane next to the dedicated lane (i.e., the middle lane) and accepted shorter gaps when lane-changing. Moreover, younger male drivers kept smaller headways compared to older female drivers. Schoenmakers et al. (2021) also studied the car-following behavior of HDVs when driving next to a dedicated lane for AVs and found that drivers maintained significantly lower headways when driving next to AV platoons driving on dedicated lanes. Fuest et al. (2020), using a driving simulator, studied the differences in perception of AVs and actual driving behavior of drivers around AVs in roadworks, traffic jams, and lane change situations, considering AV recognizability. They found that the recognizability of AVs did not affect the way they are perceived by human drivers in all situations. However, most drivers stated that they preferred that AVs would be marked (i.e., recognizable). Additionally, drivers did not change their lane change behavior (measured by the number of lane changes and time until lane change) and their car-following behavior (measured by time headway) when the AVs were recognizable versus when they were not recognizable. Stange et al. (2022) performed a driving simulator experiment to study the subjective experience and driving behavior of human drivers in mixed traffic with different appearances (using eHMIs) and penetration rate of AVs. They found that drivers experienced mixed traffic with higher AV penetration levels as less comfortable and less efficient, but not as dangerous as conventional traffic and lower AV penetration levels scenarios. Appearance differences through eHMIs did not affect driver behavior. However, drivers' average speed decreased when the AV penetration rate was 25% and higher, and the percentage of safety-critical interactions with their lead vehicle increased with increasing AV penetration rate.

Useful insights into human-AV interactions can also be derived from studies looking at vulnerable road users. Hagenzieker et al. (2020) conducted a photo experiment to study the expectations and behavioral intentions of cyclists when interacting with AVs (two types of appearances) as compared to manually driven vehicles. They found that participants were less confident to be noticed when interacting with both the AV types as compared to the manually driven vehicle, and looked significantly longer at the AVs during the first interactions. In the second interaction, participants were more confident that the AVs would stop for them. Zhao et al. (2022) studied pedestrians' intention to cross the road in front of AVs in risky situations using a questionnaire. They found that pedestrians had significantly higher intentions to cross in front of AVs as compared to HDVs. They also reported lower risk perception and greater trust in this type of vehicle.

From the existing literature, it emerges that human drivers tend to change their behavior when AVs are in their surroundings in traffic. Factors such as the AV appearance (recognizable and not recognizable), its driving style (most studies assume AVs to have shorter time headways and smoother driving profiles), personal characteristics of human drivers such as age and gender seem to affect the observed behavioral adaptation. With the increasing deployment of AVs in traffic, knowledge of such interactions at priority intersections is required, especially crucial aspects of AVs such as their recognizability and driving style. Understanding potential changes in human driving behavior in mixed AV-HDV traffic is crucial as policymakers and car manufacturers use the results of such simulation studies to take (proactive) critical decisions. In this paper, the notion of behavioral adaptation is used to describe any change in gap acceptance behavior of drivers in mixed traffic due to aspects such as recognizability and the driving style of AVs. An example of such behavioral adaptation could be that drivers accept significantly smaller gaps when they merge in front of an AV as compared to the gaps they accepted in HDV-only traffic.

4.2. Scope and research questions

This paper focuses on studying the gap acceptance behavior of human drivers in mixed traffic at priority T-intersections using a driving simulator. Following the identification of the research gaps, the main research question is defined as follows:

How do human drivers perform gap acceptance maneuvers in mixed (automated and human-driven) traffic at priority T-intersections?

To answer the main research question, the following sub-research questions were defined (considering priority T-intersections in mixed traffic):

1. Does the recognizability of AVs by itself affect human drivers' accepted gaps?
2. Does the driving style of AVs by itself affect human drivers' accepted gaps?
3. How does the recognizability and driving style of AVs, together, affect human drivers' accepted gaps?
4. How do the above factors affect human drivers' critical gaps at priority T-intersections in mixed traffic?

This research makes certain assumptions to answer the research questions. Firstly, the penetration rate of AVs is fixed at 50% to characterize a balanced HDV-AV traffic mix. Secondly, the driving behavioral differences between AVs and HDVs are defined by their desired speeds and their following time gaps. The next section explains the research methodology and elaborates on these design parameters.

4.3. Research methodology

A driving simulator experiment was designed to answer the formulated research questions. This section describes the set-up of the experiment, the experimental design, and the data collection and data processing.

4.3.1. Experiment set-up & participants' recruitment

A virtual reality experiment was set up using the driving simulator located at the Transport & Planning department, Delft University of Technology, the Netherlands. The software SCANeR (v1.9) by AV Simulation was used to design the scenarios in the driving simulator. The driving simulator, as shown in Figure 4.1, is a fixed base driving simulator comprised of a dashboard mock-up with three 4K high-resolution screens, providing approximately a 180° vision, with a Fanatec steering wheel and pedals.

Figure 4.1: A participant using the driving simulator.

The experiment also included a pre-experiment and a post-experiment questionnaire. The pre-experiment questionnaire collected information on the participants' demographics. The post-experiment questionnaire collected information on whether the participant experienced motion sickness (Kennedy et al., 1993) and their experienced presence in the simulator (Witmer & Singer, 1998) during the experiment. The experiment was approved by the Human Resource and Ethics Committee (HREC) of the Delft University of Technology.

Participants for the experiment were recruited through advertisements in social media and newspapers. Anyone with a valid driving license could participate. The experiment per participant lasted between 60 and 90 minutes, including a briefing, familiarization drive, the experiment scenarios with sufficient breaks, and post-experiment questionnaires. The participants were compensated with a voucher of 15€ each. A total of 114 participants took part in the study.

4.3.2. Route

The route was designed to allow drivers to sufficiently experience the traffic conditions before approaching the intersections. It consisted of several motorway sections, provincial (regional) road sections, and three priority T-intersections. Each T-intersection consisted of an urban road (the minor road) intersecting with a provincial road (the major road). The defined speed limit was 100 km/h on the motorway, 80 km/h on the provincial roads, and 50 km/h on urban roads. These were defined as per the current Dutch road system. Figure 4.2 depicts a sketch of the route designed in the driving simulator. This paper focuses on analyzing the behavior of the participants at the three priority T-intersections. A stop sign placed before each intersection ensured that drivers came to a full stop before navigating the intersection. These intersections are positioned towards the end of the route. This allows the participants to drive and experience different traffic conditions in the respective scenarios before reaching the intersections. Figure 4.3 shows an example situation at a T-intersection in the driving simulator environment.

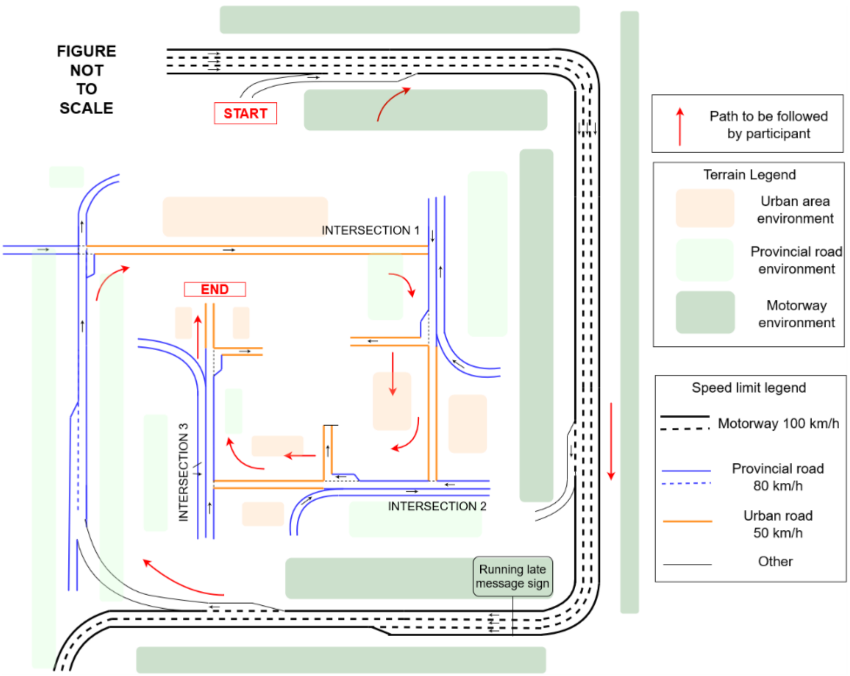

Figure 4.2: Depiction of the route driven by the participants in the experiment.

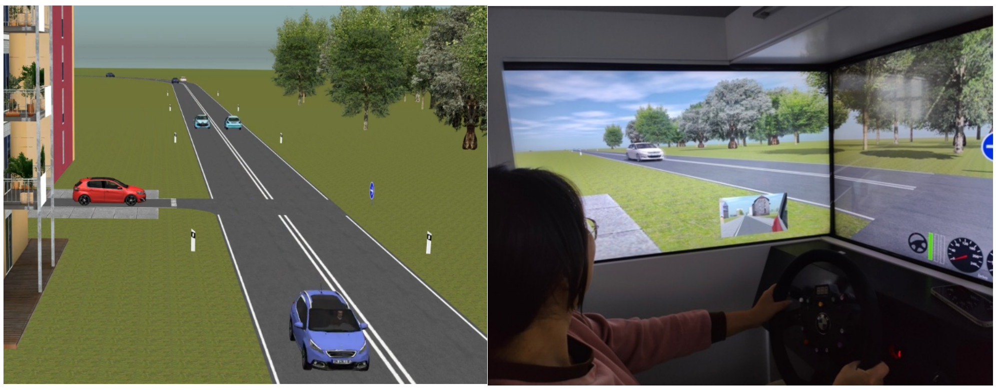

Figure 4.3: Situation at a T-intersection in the simulator (left) Driver in the red car waiting to turn right onto the major road) (right) a picture from the actual simulator where the driver is waiting to turn right.

4.3.3. Participant Groups

Two variables primarily varied in the experiment: the driving style of AVs, and their recognizability. The participants were assigned randomly to one of three groups: Defensive AVs, Aggressive AVs, and Mixed AVs. The group determined the driving style of AVs that a participant encountered in the experiment. For example, participants in the defensive AVs group only encountered defensive AVs. In the scenario of mixed AVs, both defensive and aggressive AVs were present in the volume ratio of 3:2. Throughout the experiment the penetration level of AVs was fixed at 50%. Table 4.1 shows the differences in the driving behaviors between HDVs and AVs in the experiment. The desired car-following time gap parameters of AVs were fixed based on a range of commercial ACC systems that were openly available (Makridis et al., 2021; Raju et al., 2022a). The headway for HDVs were based on (Taieb-Maimon & Shinar, 2016; Winkelbauer et al., 2019). The desired speed of both Defensive and Aggressive AVs was set to speed limit as we expect that AVs would not be explicitly designed to exceed a legal speed limit.

Table 4.1: Driving behavior parameters of AVs and HDVs in the experiment.

Vehicle	Desired speed	Desired car-following time gap (s)
HDVs	Between 90% and 110% of the speed limit, drawn randomly	Minimum 0.5; Maximum 1.5; Truncated negative exponential distribution
Defensive AVs	Set to speed limit	3.5
Aggressive AVs	Set to speed limit	1.5
Mixed AVs	This group had both Defensive and Aggressive AVs in a volume ratio of 3:2	

4.3.4. Scenarios

The experiment design aimed to separately observe the effects of AVs' recognizability and their driving style on human driving behavior as well as their combined effects. Each participant drove four scenarios, excluding a familiarization drive. The scenarios differed in two aspects: the recognizability and the driving style of AVs. Table 4.2 provides an overview of the four scenarios. Figure 4.4: Overview of the division of drivers over the three groups and depiction of the four scenarios (S1-S4)provides an overview of the groups and the scenarios.

Table 4.2: Scenarios and their definition.

Scenario number	Description	Recognizability of AVs	Driving style of AVs	Nomenclature/code
S1	Only HDVs	-	-	App (HDV) DS (HDV)
S2	HDVs & NR–AVs DS-AV	Not recognizable (NR)	AV	App (HDV) DS (AV)
S3	HDVs & R-AVs DS AV	Recognizable (R)	AV	App (AV) DS (AV)
S4	HDVs & R-AVs DS- HDV	Recognizable (R)	HDV	App (AV) DS (HDV)

*App – Appearance; DS – Driving style

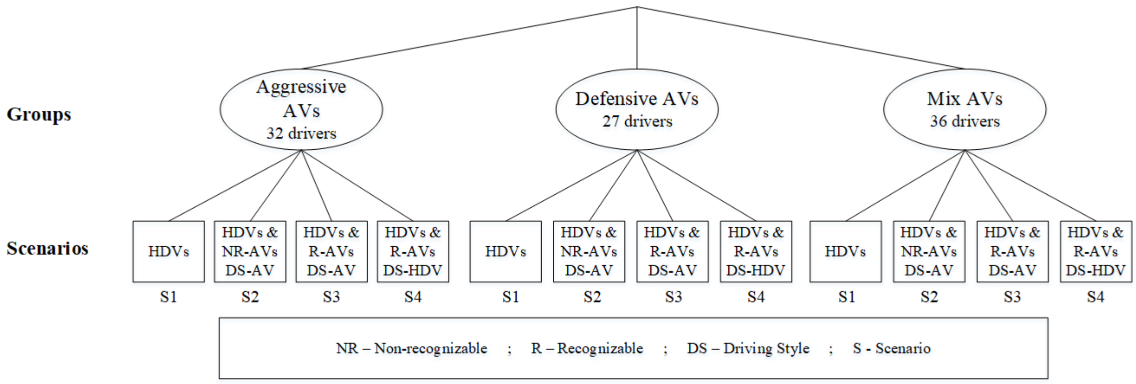

Figure 4.4: Overview of the division of drivers over the three groups and depiction of the four scenarios (S1-S4)

At the three T-intersections, traffic on the major road was generated with gaps drawn randomly between 3 and 10 seconds from a uniform distribution to ensure that the offered gaps were not too small nor too large (Beanland et al., 2013). Therefore, the distinction between Aggressive and Defensive AVs did not apply to traffic on the major road at the T-intersections. As the participants drive on the motorway and the provincial road before approaching the T-intersections, their resulting decisions of gap acceptance are expected to be influenced by the kind of traffic they interacted with in that scenario, i.e., by a "carry-over" effect. In scenarios 1 and 2, all vehicles appeared as HDVs, including the vehicles on the major roads at the T-intersections. In Scenarios 3 and 4, 50% of the traffic appeared as AVs. The vehicles on the major roads at the T-intersections can therefore appear as AVs or as HDVs in these scenarios. Figure 4.5 shows the appearance of AVs (a) and HDVs (b) in the driving simulator. Participants were informed of the appearance of AVs in the experiment and were able to differentiate AVs from the other traffic. The participants did not receive any explicit information regarding the driving style of the AVs that they will encounter. AVs in the aggressive, defensive, and mixed groups had the same appearance when they were recognizable. Each scenario lasted, on average, between 10 and 12 minutes. There were sufficient breaks provided in between scenarios. Additionally, to counter the learning effect, the participants experienced the scenarios in random order.

Figure 4.5: Appearance of vehicles in the driving simulator environment. Automated Vehicles (left) and Human-Driven Vehicles (right)

4.3.5. Experiment procedure

Before the start of the experiment, drivers signed a consent form and completed the pre-questionnaire. Then, they drove a familiarization drive to get acquainted with the driving simulator environment and the vehicle controls. After every scenario, drivers were asked to take a break. At the end of the experiment, drivers filled in the post-experiment questionnaire. In the experiment, the participating drivers were instructed to drive as they normally do on a work commute assuming they had to attend a meeting when they get there, to induce a sense of time pressure as can be expected on everyday commutes. Additionally, a message sign was displayed in the middle of the scenario and once again at the end of the motorway section (as displayed in Figure 4.2), and before approaching the priority T-intersections, stating that they were a few minutes late, to prevent drivers from being "too relaxed" in the simulator.

4.4. Data collection, data processing & analysis method

The collected data in the driving simulator contained the timestamp along with variables such as speed, acceleration, and position for every vehicle in the scenario. These raw data, which were collected at a frequency 20 Hz, was later reduced to 4 Hz to reduce processing times while still maintaining 4 data points per second. These reduced data were then processed using Python code to appropriately identify moments in time and relevant indicators for studying gap acceptance behavior. The resulting indicators from the simulator data were then matched to the appropriate questionnaire responses by the participants. The analysis was divided into two parts: accepted gap analysis, and critical gap analysis.

T-intersections are generally characterized by two conflicting roads, a major road, and a minor road, according to the magnitude of their traffic volumes. When a sufficient gap arises on the major road, drivers on the minor road accept the gap by merging onto the major road. The vehicle on the major road that the minor road driver merges in front of is termed the "follower", and the vehicle in front of the driver after accepting the gap is termed the "leader". The gap that is accepted is termed as "accepted gap", defined as the time gap (in seconds) between the front of the follower and the rear of the leader. The gaps that the drivers do not accept are termed "rejected gaps". Drivers are also presumed to have a critical gap which is the minimum gap they are willing to accept. The critical gap is a hard threshold below which the driver always rejects the gap. Accepted gaps and rejected gaps can be observed, but the critical gap can only be estimated. In this research, the accepted gap analysis consisted of statistical testing and modeling. Wherever relevant, analyses were separated according to within groups/scenarios and between groups/scenarios. Appropriate statistical tests were used, such as the Friedman's Test (comparing means of multiple scenarios within subjects), the Wilcoxon Signed Ranks Test (post hoc analysis after Friedman's Test), the Kruskal-Wallis Test (comparing means of groups between subjects), the Mann-Whitney Test (Post hoc analysis after Kruskal Wallis Test), and the Levene's Test (comparing variance between subjects). For modeling, a generalized linear model was adopted. The critical gap estimation was performed using Wu's method (Wu, 2006). This method was found to give similar results of the mean critical gap as compared to the Maximum Likelihood, and without requiring any major assumptions on the consistency and homogeneity of drivers (Amin & Maurya, 2015). However, to use the method, the minimum accepted gap must be smaller than the maximum rejected gap. Statistical testing of the estimated critical gaps was performed using the Kolmogorov–Smirnov test. The significance level was kept at 0.05.

While presenting the results, specific nomenclature is used. The four scenarios differ in the appearance (App) of the AVs and their driving styles (DS). As an example, App (AV) DS (HDV) describes the scenario where AVs appear as AVs (that is, they are recognizable) and drive the same as HDVs. At the intersections, it is also interesting to study the type of vehicle the participant merged in front of, that is, the immediately following vehicle after the participant accepts a gap. The appearance of this vehicle could be AV or HDV. The results also present an analysis of gap acceptance for different types of followers within the same scenario. For instance, App (AV) DS (AV) Follower App (HDV) describes the gap acceptance observations for the scenario where AVs were recognizable, driving according to the AV driving style, but the participant accepted a gap at the intersection in front of an HDV. As there are three groups, namely Aggressive (Agg), Defensive (Def), and Mixed (Mix) AVs, this may also be specified in the nomenclature as DS (Agg AV), DS (Def AV), or DS (Mix AV), respectively.

4.5. Results

The results are structured as follows. First, the gender and age distributions of the participants are shown. Next, descriptive statistics of accepted gaps at the three intersections, for the different scenarios and groups are presented. Then, the analyses and results for each sub-research question are presented separately.

4.5.1. Participants

Of the 114 participants who participated, 12 (10.5%) experienced severe nausea and/or were unable to complete the experiment, and therefore were excluded from the analysis. Moreover, 7 participants were also excluded due to erroneous behavior at the intersections (not following instructions), or for very poor driving behavior (abnormal driving). This resulted in a final gap acceptance dataset of 95 participants of which 71 (74.7%) were male and 24 females. Figure 4.6 (left) shows the distribution of the participants by age group. The age groups were combined into three age categories: Younger (18-29), Middle-aged (30-54), and Older (55+) to ensure a reasonable number in each category. It was also attempted to have both gender groups in each of these age categories (Figure 4.6 (right)).

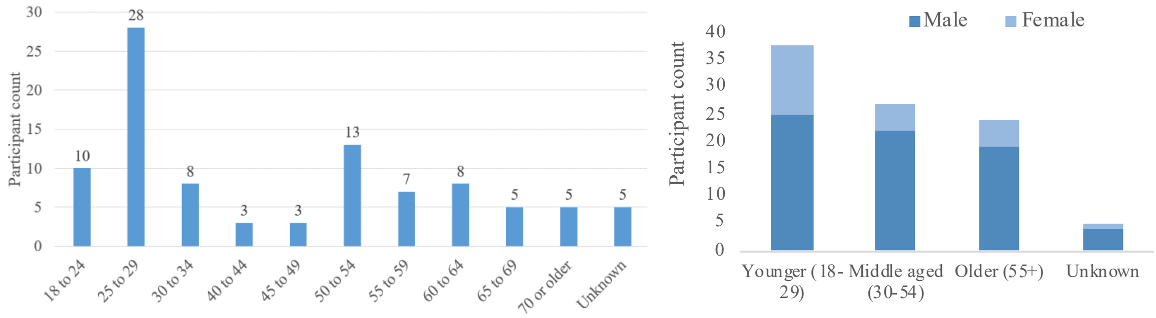

Figure 4.6: Age group distribution (95 participants) (left); Participants split between age categories and gender (right).

4.5.2. Descriptive statistics of accepted gaps

Table 4.3 shows the number of accepted gap and rejected gap observations recorded for different conditions in the experiment. The total number of accepted gap observations in the dataset is 948 (excluding the familiarization drive).

Table 4.3: The number of Gap Acceptance Observations in the Dataset.

Condition	Number of accepted gap observations	Number of rejected gap observations	% Accepted gaps
Complete dataset	948	2092	31%
App (HDV) DS (HDV)	242	524	32%
App (HDV) DS (AV)	240	501	32%
App (AV) DS (AV)	241	569	30%
App (AV) DS (HDV)	225	498	31%
Def	269	608	31%
Agg	318	760	29%
Mix	361	724	33%
Follower App (HDV)	709	1537	32%
Follower App (AV)	239	555	30%

In this study, gap acceptance behavior is measured by the total accepted gap (in seconds), henceforth referred to as just the “accepted gap”. Accepted gap is defined by the sum of the lag (with follower) and the lead (with leader) time gap at the instant the subject vehicle entered the major road. This is calculated using the speed and distance to the intersection of the leader and follower vehicles at the instant the subject vehicle entered the major road. The speeds of the vehicles on the major road were constant until the subject vehicle merged into the major road. For statistical analysis, the three accepted gap observations at the three intersections for every scenario (for every participant) were averaged. The mean accepted gaps at the three intersections ranged between 7.13 s and 7.31 s with the standard deviation ranging between 1.44 s and 1.55 s. Friedman’s test showed that there was no statistically significant difference in the accepted gaps between the three intersections $\chi2(3) = 2.831$, $p = 0.243$. Therefore, no significant information was lost by averaging the observations at the three intersections. However, for modeling, observations at all three intersections were considered.

4.5.3. Does the AV recognizability by itself affect drivers’ accepted gaps?

For statistically testing the effect of AV recognizability by itself, first, the accepted gaps of scenarios App (AV) DS (AV) and App (HDV) DS (AV) were compared for each of the three groups, that is, aggressive, defensive, and mixed. Table 4.4 presents the median and standard deviation of the accepted gaps for the two scenarios for the three groups as well as the Wilcoxon signed rank test results.

There were no significant differences found in the accepted gaps between the two scenarios for the defensive, aggressive, and mixed groups. This suggested that irrespective of the driving style of AVs, their recognizability did not significantly affect drivers' accepted gaps. The difference for the aggressive group, however, was close to being significant (at the 95% confidence level). The same was tested for different age and gender categories. There were no significant differences for any of the categories.

The two scenarios App (AV) DS (HDV) and App (HDV) DS (HDV) were also compared for each of the three groups. The results are presented in Table 4.4. There were no significant differences found in the accepted gaps for these two scenarios for the defensive, the aggressive, and the mixed groups. This suggests that when AVs have the same driving style as HDVs, their appearance by itself does not have a significant effect on human drivers' accepted gaps.

Table 4.4: Accepted gaps for scenarios App (AV) DS (AV) and App (HDV) DS (AV) within the three groups.

Group	Median (and standard deviation) of accepted gap		
	App (AV) DS (AV)	**App (HDV) DS (AV)**	**Wilcoxon signed rank test**
Defensive AV Group	7.43 (0.79)	6.89 (0.82)	Z = -0.179, p = 0.858
Aggressive AV Group	7.97 (0.93)	6.98 (0.89)	Z = -1.825, p = 0.068
Mixed AV Group	7.32 (0.97)	7.28 (1.18)	Z = -0.168, p = 0.866
	App (AV) DS (HDV)	**App (HDV) DS (HDV)**	
Defensive AV Group	6.89 (0.82)	7.22 (0.96)	Z = -0.155, p = 0.877
Aggressive AV Group	6.98 (0.89)	7.82 (1.19)	Z = -0.958, p = 0.338
Mixed AV Group	7.28 (1.18)	7.33 (1.06)	Z = -0.308, p = 0.758

4.5.4. Does the AV driving style by itself affect drivers' accepted gaps?

For statistically testing the effect of AV driving style by itself, the accepted gaps of the defensive, aggressive, and mixed groups were compared for the scenarios App (AV) DS (AV) and App (HDV) DS (AV). The Kruskal Wallis test was used to test the differences between the three groups for the two scenarios. Table 4.5 presents these results. Both scenarios App (AV) DS (AV) and App (HDV) DS (AV) were not significantly different between the three groups. This suggests that the AV driving style by itself does not affect drivers' accepted gaps, for both recognizable and unrecognizable AVs.

The same was tested for the different age and gender categories for the two scenarios. No significant differences were observed between the three groups for any of the age and gender categories.

Table 4.5: Accepted gaps for scenarios App (AV) DS (AV) and App (HDV) DS (AV) between the three groups.

Scenario	Median (and standard deviation) of accepted gap for different groups			
	Defensive	**Aggressive**	**Mixed**	**Kruskal-Wallis test**
App (AV) DS (AV)	7.43 (0.79)	7.97 (0.93)	7.32 (0.97)	H (2) = 2.965, p = 0.227
App (HDV) DS (AV)	6.89 (0.82)	6.98 (0.89)	7.28 (1.18)	H(2) = 1.528, p = 0.466

4.5.5. How do the recognizability and driving style of AVs, together, affect drivers' accepted gaps?

Figure 4.7 presents the box plot of accepted gaps for scenario-group combinations. In Figure 4.7, driving styles are color coded so that the groups with aggressive AVs are in a range of red, those with defensive AVs are in a range of green, and those with mixed AVs are in a range of blue. HDVs are color-coded in a range of grey. The lighter and darker shades indicate whether the AVs are non-recognizable or recognizable, respectively. It is observed that drivers accept larger gaps when interacting with a vehicle that appears as an AV and has an aggressive driving style (App (AV) DS (Agg AV)).

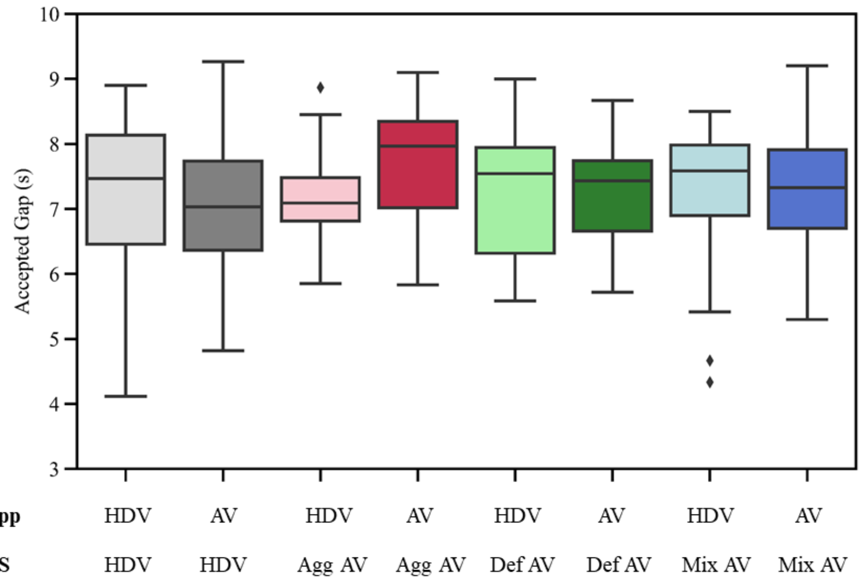

Figure 4.7: Accepted gap for different scenario-groups (boxplots illustrate the distribution of the data represented by the "minimum", first quartile (Q1), median, third quartile (Q3), and the "maximum". The dots (outside the whiskers) indicate outliers.

A generalized linear model was estimated to understand the effects of recognizability and driving style on the accepted gaps. For this, accepted gap observations from scenarios App (AV) DS (AV) and App (HDV) DS (AV) were used. Table 4.6 presents the estimated model. The reference condition is App (AV) Follower App (AV) DS (Agg AV). The model contains three types of terms: first, the combination of appearance (App) and follower appearance (Follower App), second, the AV driving style (DS), and third, the interaction between these two terms. Drivers accept smaller gaps when driving in the conditions App (AV) Follower App (HDV) and App (HDV) Follower App (HDV) compared to the gaps they accept in the App (AV) Follower App (AV) condition. Drivers also tend to accept smaller gaps in the condition DS (Def AV) and DS (Mix AV) compared to the DS (Agg AV) condition. Considering the interaction terms, the condition App (AV) Follower App (AV) with DS (Agg AV) results in the largest accepted gaps compared to any other condition.

Table 4.6: Generalized linear model results for accepted gap for scenarios App (AV) DS (AV) and App (HDV) DS (AV).

Coefficients	Estimate	Std. error	t value	Pr (>|t|)
(Intercept)	7.918	0.236	33.556	< 2e-16 ***
App (AV) Follower App (HDV)	-0.738	0.355	-2.079	0.038 *
App (HDV) Follower App (HDV)	-0.817	0.293	-2.790	0.005 **
DS (Def)	-0.862	0.374	-2.302	0.021 *
DS (Mix)	-1.004	0.315	-3.181	0.001 **
App (AV) Follower App (HDV) DS (Def AV)	1.022	0.516	1.980	0.048 *
App (HDV) Follower App (HDV) DS (Def AV)	0.975	0.452	2.156	0.031 *
App (AV) Follower App (HDV) DS (Mix AV)	1.403	0.466	3.011	0.002 **
App (HDV) Follower App (HDV) DS (Mix AV)	1.157	0.390	2.963	0.003 **
AIC: 1621.6				

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

In Figure 4.8, the respective scenario-group (indicated by App and DS) and follower appearance (indicated by Follower App) for each boxplot is indicated by a tabular x axis label. It can be observed that the median accepted gap for the case App (AV) DS (Agg AV) Follower App (AV) is the highest.

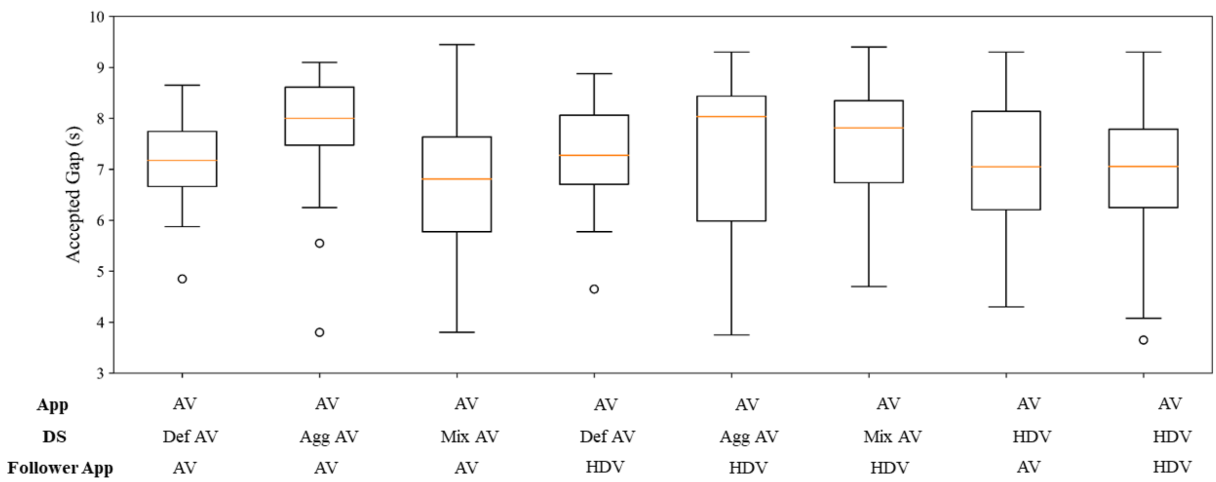

Figure 4.8: Accepted gap for different scenario-group-follower appearance combinations.

4.5.6. How do the above factors affect human drivers’ critical gaps at priority T-intersections in mixed traffic?

Wu’s method was used to estimate the critical gaps for different conditions. Wu’s method provides cumulative distribution functions for the critical gaps. Figure 4.9 presents an example of the cumulative density functions of rejected, critical, and accepted gaps for the App (AV) DS (AV) condition. Figure 4.10 presents the cumulative density functions of critical gaps for different conditions.

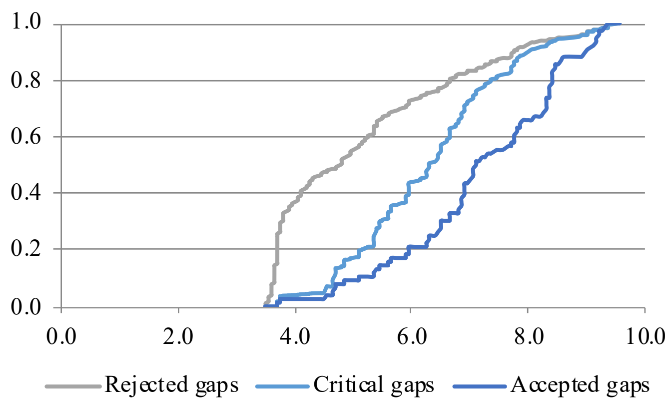

Figure 4.9: CDF of rejected, critical, and accepted gaps for the App (AV) DS (AV) condition

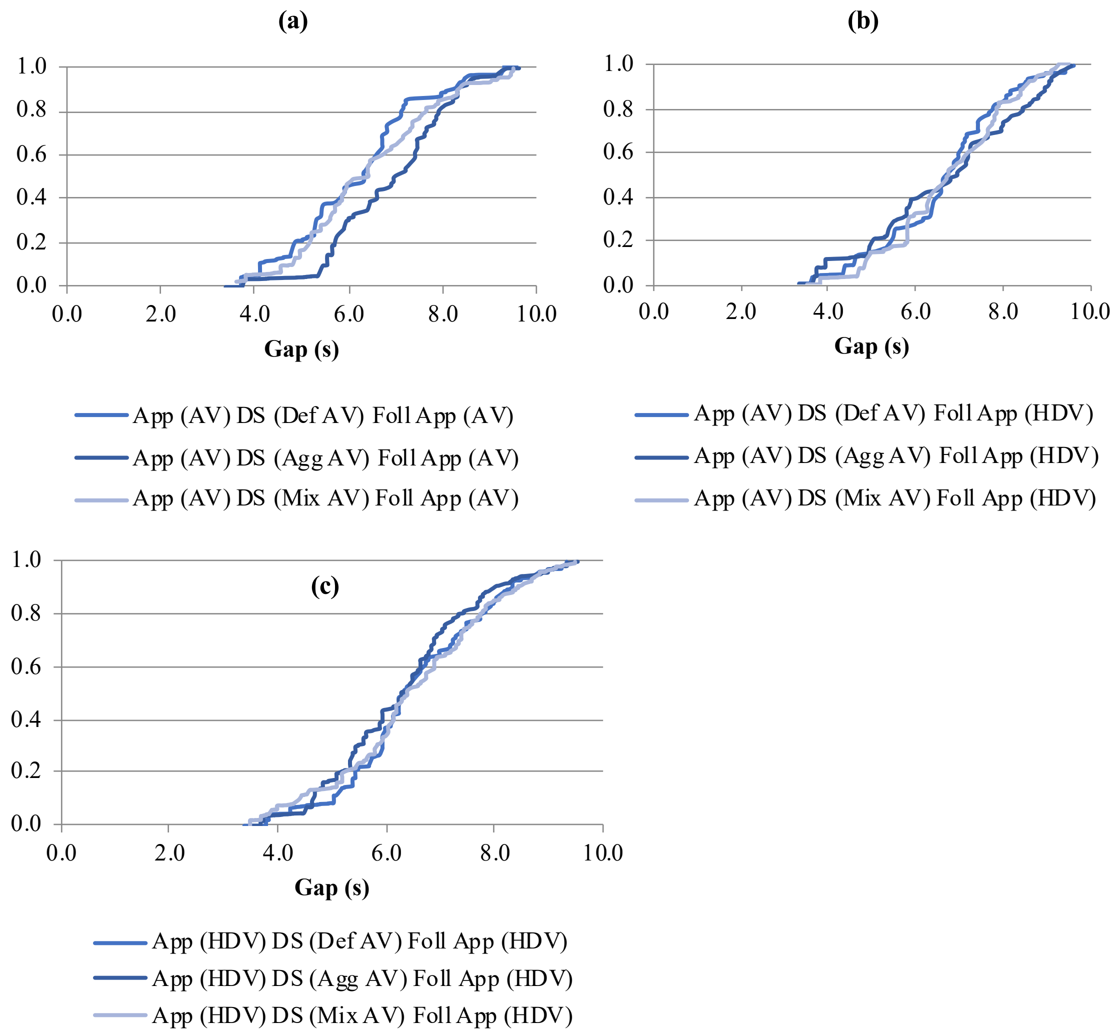

Figure 4.10: CDF of critical gaps for different groups (recognizable AVs) when merging in front of (a) an AV follower, (b) an HDV follower, and (c) when in traffic with non-recognizable AVs.

The mean and standard deviation of the distributions can also be computed. Table 4.7 presents the calculated mean and standard deviations of the critical gaps for different conditions. As can be noticed the mean critical gap for the scenario App (AV) DS (Def AV) Follower App (AV) is the lowest, while for App (AV) DS (Agg AV) Follower App (AV) is the highest. The 2-sample Kolmogorov–Smirnov test was used to test differences between the distributions of critical gaps of different conditions. As the KS test assumes independent samples, groups of conditions, described in Table 4.7, that could be compared were (5, 6, 7), (8, 9, 10), (11, 12, 13), (14, 15, 16), (17, 18), and (19, 20, 21).

Table 4.7: Critical gap mean and standard deviation for different conditions

Condition no.	Description	Critical gap (s)	
		Mean	**SD**
Scenarios			
1	App (HDV) DS (HDV)	6.43	1.43
2	App (HDV) DS (AV)	6.44	1.36
3	App (AV) DS (AV)	6.59	1.42
4	App (AV) DS (HDV)	6.33	1.52
Groups			
5	Def	6.43	1.42
6	Agg	6.41	1.42
7	Mix	6.51	1.46
Scenario-Group-Follower App			
8	App (AV) DS (Def AV) Follower App (AV)	6.15	1.38
9	App (AV) DS (Agg AV) Follower App (AV)	6.86	1.22
10	App (AV) DS (Mix AV) Follower App (AV)	6.32	1.64
11	App (AV) DS (Def AV) Follower App (HDV)	6.66	1.37
12	App (AV) DS (Agg AV) Follower App (HDV)	6.69	1.69
13	App (AV) DS (Mix AV) Follower App (HDV)	6.76	1.34
14	App (HDV) DS (Def AV) Follower App (HDV)	6.53	1.30
15	App (HDV) DS (Agg AV) Follower App (HDV)	6.31	1.30
16	App (HDV) DS (Mix AV) Follower App (HDV)	6.48	1.43
Gender and age			
17	Female drivers	6.50	1.46
18	Male drivers	6.44	1.41
19	Younger drivers	6.40	1.47
20	Middle-aged drivers	6.49	1.41
21	Older drivers	6.43	1.33

The 2-sample K-S test was used to check significant differences. As Wu's method yields the cumulative density function values the 2-sample KS test was manually performed in Python. Using linear interpolation, the CDF values for the same gap sizes were computed and their difference was measured between two conditions. Table 4.8 presents the results with the largest difference (D-statistic) and the critical D values for the conducted tests. Firstly, there was no significant difference between the different groups (i.e., conditions 5, 6, and 7). This indicated that at an aggregate level over all the scenarios, critical gaps of drivers in the defensive, aggressive, and mixed group were not significantly different. Secondly, when merging in front of a recognizable AV, the critical gap of drivers driving in the recognizable and aggressive AV traffic environment (i.e., condition 9) is significantly larger than that of drivers driving in the defensive and mixed traffic environment (i.e., conditions 8 and 10). A significant difference in critical gaps was also found between defensive (i.e., condition 14) and aggressive (i.e., condition 15) AV traffic when AVs were not recognizable. Interestingly here, the critical gaps in the aggressive condition were smaller than in the defensive condition. This suggests that drivers tended to follow headways of the surrounding traffic when aggressive AVs were not recognizable. There was no significant difference between conditions 11, 12, 13 and between conditions 14, 16 and 15,16. This indicates that when merging in front of an HDV, there was no difference in the critical gap of drivers when driving in Defensive, Aggressive, or Mixed recognizable AV traffic. There was also no significant difference in the critical gap of drivers between Defensive and Mixed non-recognizable AV traffic. Testing between gender and age groups revealed no significant difference between Female and Male drivers and no significant difference between Younger, Middle-aged, and Older drivers. This indicates that gender and age did not affect critical gaps.

Table 4.8: Critical gap mean and standard deviation for different conditions.

Condition 1	Condition 2	D-stat	Critical D	Inference on distributions
Def	Agg	0.041	0.070	Similar
Def	Mix	0.046	0.070	Similar
Agg	Mix	0.056	0.067	Similar
(AV)(Def AV)(AV)*	(AV)(Agg AV)(AV)*	0.300	0.169	Different
(AV)(Def AV)(AV)*	(AV)(Mix AV)(AV)*	0.144	0.176	Similar
(AV)(Agg AV)(AV)*	(AV)(Mix AV)(AV)*	0.205	0.158	Different
(AV)(Def AV)(HDV)*	(AV)(Agg AV)(HDV)*	0.128	0.181	Similar
(AV)(Def AV)(HDV)*	(AV)(Mix AV)(HDV)*	0.113	0.166	Similar
(AV)(Agg AV)(HDV)*	(AV)(Mix AV)(HDV)*	0.131	0.176	Similar
(HDV)(Def AV)(HDV)*	(HDV)(Agg AV)(HDV)*	0.131	0.130	Different
(HDV)(Def AV)(HDV)*	(HDV)(Mix AV)(HDV)*	0.065	0.129	Similar
(HDV)(Agg AV)(HDV)*	(HDV)(Mix AV)(HDV)*	0.118	0.123	Similar
Female	Male	0.034	0.064	Similar
Younger	Middle-aged	0.057	0.066	Similar
Younger	Older	0.057	0.074	Similar
Middle-aged	Older	0.054	0.080	Similar

*(Appearance)(Driving style)(Follower appearance)

4.6. Discussion & conclusions

A driving simulator experiment was designed to study whether and how the recognizability and the driving style of AVs affect (HDV) drivers' accepted gaps and critical gaps at priority T-intersections. This section first summarizes the key findings as answers to the research questions and then reflects on these findings with respect to findings from previous studies. The study's limitations are also discussed.

4.6.1. Summary of findings

Testing the effect of recognizability of AVs (research question 1) revealed that recognizability by itself did not have any effect on the accepted gaps. This is the case as well for each of the three groups (aggressive AVs, defensive AVs, mixed AVs), indicating that for all of the three groups recognizability by itself did not affect drivers' accepted gaps, irrespective of whether the AVs drove like HDVs or according to their respective AV driving style. However, drivers were observed to have close to significantly larger gaps when aggressive AVs were recognizable compared to when they were not recognizable. No effects of recognizability were found also for any age and gender category.

Testing the effect of driving style of AVs (research question 2) revealed that the driving style by itself did not have any effect on drivers' accepted gaps. No significant differences in accepted gaps were observed between aggressive, defensive, and mixed AV driving styles. This was the case for both when the AVs were recognizable and when they were not recognizable. No significant effects of AV driving style were found for the age and gender categories.

The combined effect of recognizability and driving style of AVs, along with the appearance of the follower (research questions 3) was tested. AVs driving according to aggressive style tended to result in significantly larger accepted gaps than defensive or mixed AVs. When AVs were not recognizable, or when they were recognizable, but the follower vehicle was an HDV, accepted gaps tended to be smaller than when AVs were recognizable, and the follower vehicle was an AV. The largest accepted gaps were observed when AVs were recognizable, driving according to the aggressive style, and the follower was an AV.

Studying the effect on the critical gap (research question 4) revealed that the critical gaps were not significantly different at an aggregate level over all scenarios between the defensive, aggressive, and mixed AV groups. Critical gaps of drivers in aggressive and recognizable AV traffic were significantly larger than those in defensive and mixed recognizable AV traffic when merging in front of a recognizable AV. This was similar to the accepted gaps analysis. When traffic had recognizable AVs, critical gaps of drivers when merging in front of an HDV were not significantly different between defensive, aggressive, and mixed AV traffic. For this condition, it may be noted that the standard deviation of the critical gaps in the aggressive group stood out (1.69) compared to the defensive (1.37) and the mixed group (1.34). A similar observation was made in the accepted gaps analysis. However, when traffic had non-recognizable AVs, critical gaps of drivers were significantly smaller when traffic was composed of aggressive AVs as compared to defensive AVs. This indicates that when traffic has recognizable AVs, their aggressive driving style may induce defensive driving behavior among human drivers as suggested by the increase in their critical gaps. When traffic has non-recognizable AVs, their aggressive driving style may induce aggressive driving among human drivers as suggested by the decrease in their critical gaps. This indicates that aggressive driving style and recognizability of AVs, together affect the critical gap of drivers at T-intersections. Gender and age group did not affect drivers' critical gaps.

4.6.2. Discussion

While (Trende et al., 2019) and (Soni, 2020) found drivers willing to accept shorter gaps in front of AVs, drivers in this experiment accepted larger gaps in front of AVs only when AVs were aggressive and recognizable. When AVs were not recognizable, drivers' critical gaps were smaller when AVs were aggressive compared to defensive. This suggests that the interaction of recognizability and driving style of AVs is important to consider. It is interesting to note that in (Trende et al., 2019) and (Soni, 2020), drivers were provided information to bias their perception of AVs, and in this experiment, driving on the route before the intersections likely affected the perception of AVs. While conclusive comparisons are difficult to draw, a common underlying perceptual mechanism that makes drivers accept larger/smaller gaps when they perceive AVs as relatively unsafe/safe respectively cannot be ruled out. An interesting observation was that aggressive AVs induce more defensive (larger critical gap) driving among human drivers when they are recognizable and induce more aggressive (smaller critical gap) driving when they are not recognizable. Besides comparing the results of this study with previous gap acceptance related research, it is also difficult to reflect on previous studies on car-following behavior as behavioral adaptations in this experiment occurred due to the "carry-over effect" of driving before approaching the intersections. This could also be the reason for the many statistically insignificant findings. Drivers first drove on the route and interacted with traffic, including AVs before they reached and navigated the intersections. Therefore, any behavioral adaptation that could have occurred would be shaped by the drivers' experience before approaching the intersections. It may be expected that there would be more noticeable effects in other behaviors such as car-following or lane-changing where there is more "live" interaction between the drivers and the surrounding traffic. At the same time, statistical insignificance is by itself an important finding that suggests a lack of strong effect of a particular factor. Still, further research that targeted on some of the factors addressed in this research can lead to findings that can yield statistically significant effects. Along with the results of this study, the study limitations are important to consider. Firstly, the driving behavior of AVs of different driving styles was defined only using a desired car-following time gap parameter. That is, a specifically chosen car-following and lane-changing models were not used. Secondly, the appearance of AVs could have had some effect on their perceived (un)safety. The model and the color of the AVs used in this experiment could have affected the way they were perceived. These were, however, not changed between Defensive and Aggressive AVs. Thirdly, the realism of simulator environments has always been much debated. The control equipment such as the steering wheel and the gas and brake pedals were experienced by participants to be slightly different from their real-world driving experience. Also, the time pressure that drivers felt in the simulator could be different from real-world driving. Still, any potential simulator learning effect was attempted to be compensated by randomizing the scenarios and having a familiarization drive at the start. Additionally, translation of such simulator-environment results into real-world results needs to be done carefully, one of the reasons being the much lower experienced risk in a simulator compared to reality. Finally, although a decent number of participants took part in the study, the sample size may still not have been large enough to satisfactorily check the several considered variables.

4.7. Future research and implications for practice

Future work should study gap acceptance behavior with traffic present on the approach road, both lead and lag gaps. Gap acceptance behavior at left turns where drivers need to consider the traffic from both directions before accepting a gap increases the complexity of the gap acceptance behavior and would be an important direction to explore. In addition, the effect of different penetration levels of AVs in traffic could have implications on the magnitude of human drivers' behavioral adaptation. Given such behavioral adaptation of human drivers around AVs, AV drivers could have different preferences concerning, for example, ACC settings. Decisions of AV drivers in combination with the resulting behavioral adaptations of human drivers are expected to affect traffic efficiency and safety, and therefore important to study. For instance, short (aggressive) headway settings of AVs can be expected to increase traffic efficiency. This must, however, be weighed against the decrease in traffic efficiency caused by defensive maneuvers of other human drivers when AVs are recognizable.

When short (aggressive) headway settings are active for the ACC of recognizable AVs, other human drivers perform maneuvers further away from the AV. This may encourage AV users to keep such short settings as their individual travel experience could become better. This could suggest the exploitation of other (HDV) traffic by AV users. On the contrary, when aggressive AVs were not-recognizable, other human drivers performed more aggressive maneuvers. This could lead to the exploitation of AVs by other human drivers. At the same time, in (Trende et al., 2019) and (Soni, 2020), drivers were observed to perform closer maneuvers around AVs when they are recognizable when drivers have a positive opinion of AVs. This may also be the case when longer (defensive) headway settings are active for the ACC of recognizable AVs. Therefore, other human drivers could exploit AVs also when they are recognizable. Vehicle manufacturers could consider monitoring the attention of AV drivers more frequently, so they are prepared to take over if necessary. External Human-Machine Interfaces could also be a way to control risky cut-ins by other HDVs. One important implication from this study is that if AVs drive aggressively, a behavioral adaptation of other human drivers is most likely to occur both when they are recognizable and not recognizable.

Road authorities are increasingly considering Infrastructure to Vehicle (I2V) communication. Such information could not only include the state of the road downstream, but also explicit instructions for the AV to drive in a certain way. When authorities provide such instructions to AVs in mixed traffic, they need to consider the possible behavioral adaptations. For instance, asking (recognizable) AVs to decrease their headway could cause HDVs to drive in a way that can even decrease traffic efficiency. On the other hand, asking (recognizable) AVs to increase their headway may cause other HDVs to perform risky maneuvers. Examples of V2I situations where this could be relevant are the provision of Variable Speed Limits to AVs upstream, and the provision of time to green information from intelligent intersection controllers to AVs.

4.8. References

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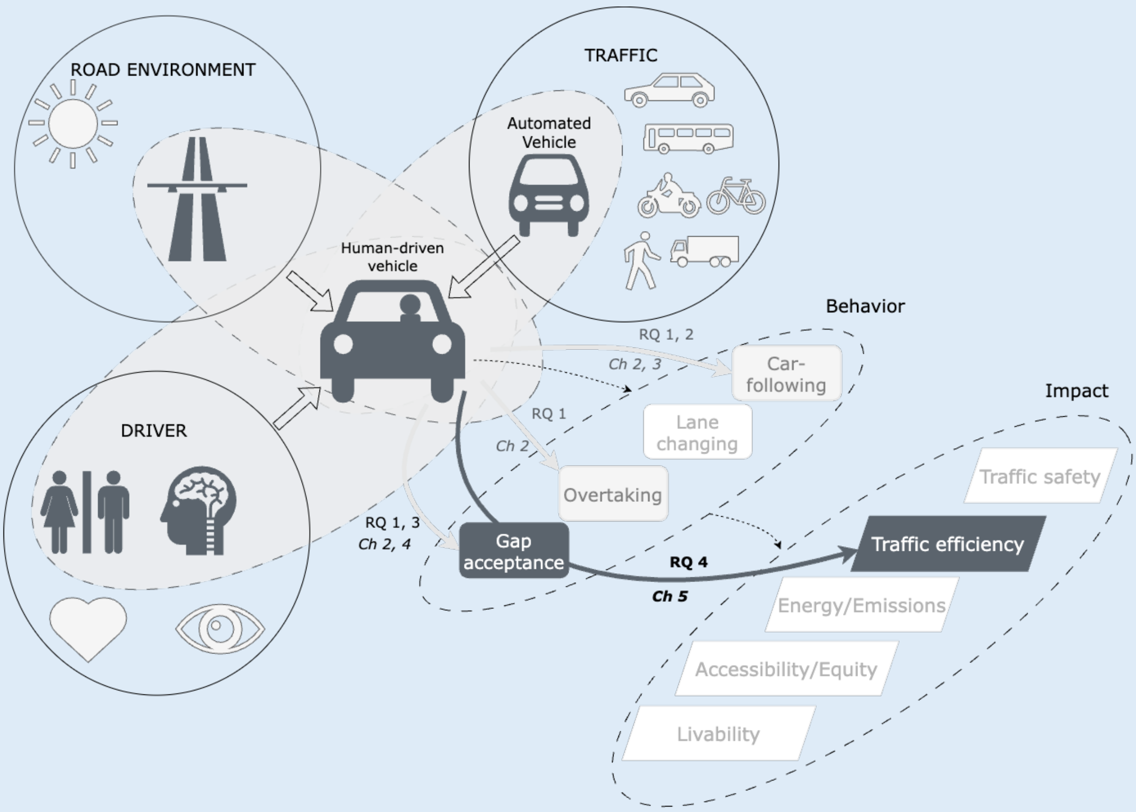
Chapter 5:

Investigating the impact of behavioral adaptation on traffic efficiency: A microsimulation approach

In Chapter 4, we investigated human drivers’ gap acceptance behavior in mixed traffic. In Chapter 5, we model human drivers’ gap acceptance behavior and implement that in a traffic microsimulation network. Here, we studied the impact of automated vehicles’ recognizability, their driving style, and their penetration rate on the traffic efficiency of the intersection.



Highlights

- We studied drivers' gap acceptance behavior at T-intersections in mixed traffic
- The observed behavior in the driving simulator was modelled in SUMO microsimulation
- Delay for minor road vehicles increased with AV penetration rate on the major road
- The recognizability of aggressive AVs increased the delay for minor road vehicles
- Ignoring behavioral adaptation underestimates the minor vehicle's delay by up to 75%

This chapter is based on the publication: 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). https://doi.org/10.59490/ejtir.2025.25.2.7557

Chapter 5
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5. Investigating the impact of behavioral adaptation on traffic efficiency: A microsimulation approach

5.1. 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 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.

5.1.1. 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., 2014a; Razmi Rad et al., 2021; Schoenmakers et al., 2021b). 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.

5.1.2. 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.

5.1.3. 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:

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

In our previous study (Reddy et al., 2022), we 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.

5.2. 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 5.3 the driving simulator experiment used to collect data of human drivers' gap acceptance behavior in mixed traffic. Then in Section 5.4 we present the results of the estimated gap acceptance models using the collected data. In Section 5.5 we explain the set-up of the microscopic traffic simulation experiments. Then in Section 5.6 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.

5.3. 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).

5.3.1. 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.

5.3.2. Route

The route (depicted in Figure 5.1) 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.

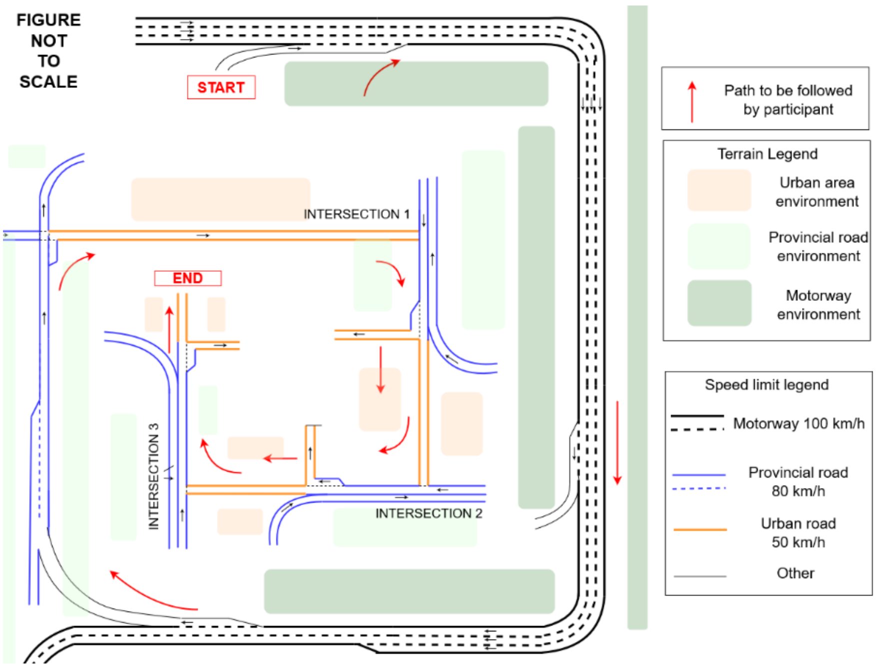

Figure 5.1: A sketch of the route in the driving simulator (Reddy et al., 2022).

5.3.3. Experiment design

Scenarios in the experiment differed in the AVs' recognizability and their driving styles. Each participant experienced four scenarios. Table 5.1 shows a description of the scenarios.

Table 5.1: Description of Scenarios

Number	Vehicle types	Were AVs Recognizable?	AV 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 5.2. 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 5.2: 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.

5.3.4. 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.

5.4. Gap acceptance modelling and estimation

5.4.1. 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 5.1 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 5.1from 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 5.1 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 5.3 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 5.3: 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.

5.4.2. Modelling results

Table 5.4, Table 5.5, and Table 5.6 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:

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

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

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 5.4: 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 5.5: 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 5.6: 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			

5.4.3. Insights from the models

It can be observed from the gap acceptance model for the conventional traffic (Table 5.4) 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 5.5), 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 5.6), 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.

5.5. 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 Traffic Control Interface). 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 of this chapter, in Figure A-1 which describes the TRACI python script, the simulation set-up and data outcome.

5.5.1. Network

The designed road network (Figure 5.2) 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.

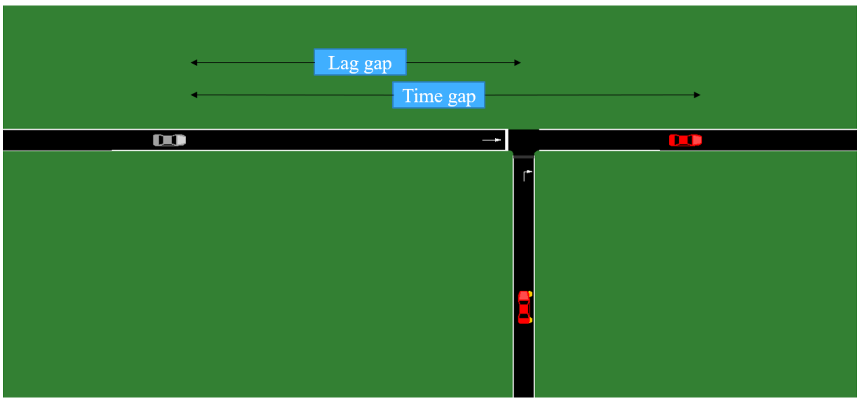

Figure 5.2: T-intersection in SUMO with a vehicle on the minor road and two vehicles on the major road.

5.5.2. Vehicle types and attributes

Major road: Traffic on the major road consisted of both HDVs and AVs. Table 5.7 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 5.3 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 5.4, 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 5.7 (additionally, the following parameters were used: Delta = 4, Tau = 0.5 s, Acceleration = 2.6 m/s2). Equations 3 and 4 represent the IDM.

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

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

Where $\dot{v}_\alpha$ is the acceleration, $a^{(\alpha)}$ is the maximum acceleration, v_α 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_α 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.

Table 5.7: 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

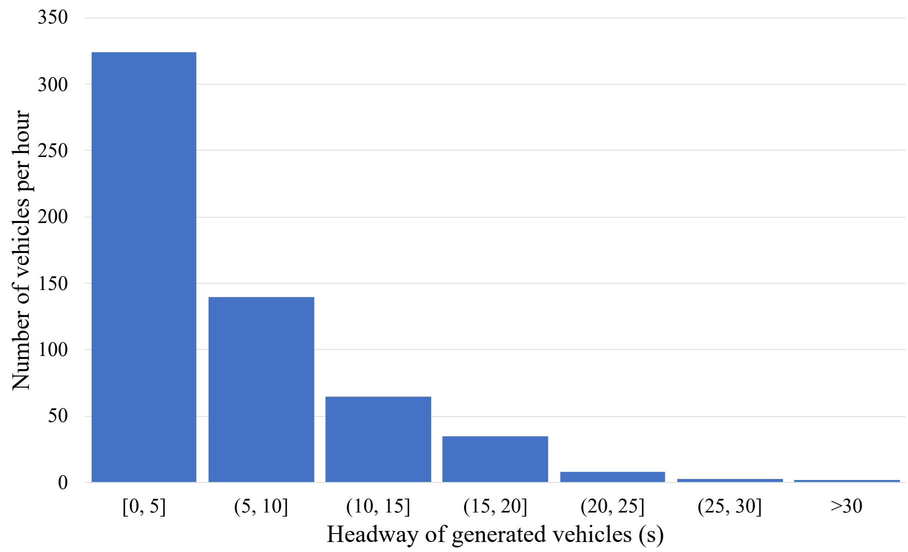

Figure 5.3: Headway distribution of all vehicles generated on the major road.

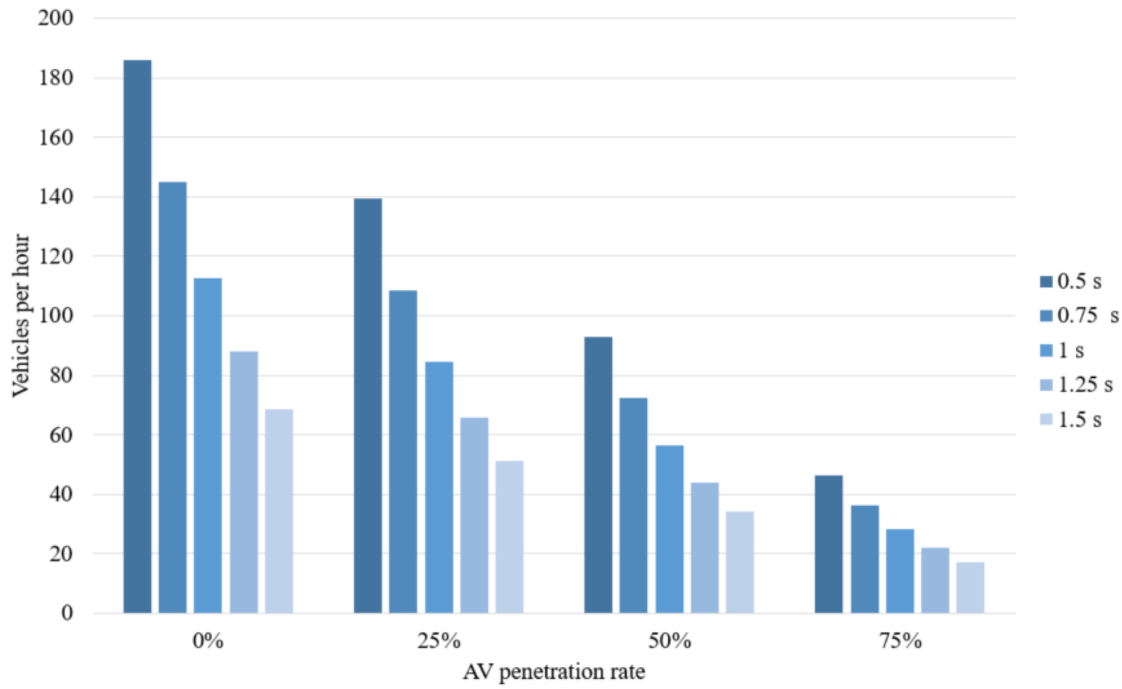

Figure 5.4: Major road volume distribution of HDVs with different desired time headways at different AV penetration rates.

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/s2. Their gap acceptance behavior was as per the estimated models (Table 5.3, Table 5.4, Table 5.5). 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.

5.5.3. 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 5.8 presents these variables with their defined levels. Additionally, consideration of behavioral adaptation was also incorporated in these conditions.

Table 5.8: 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 5.9.

Table 5.9: Simulation conditions definitions

Condition number	Code MPR_DS_R_BA*	AV MPR*	AV driving style*	AV recognizability*	Behavioral Adaptation*
1	Conventional	-	-	-	-
2	25_LD_NoBA	25%	LD	NR	NoBA
3	25_MD_NoBA		MD		
4	50_ LD _NoBA	50%	LD		
5	50_ MD _NoBA		MD		
6	75_ LD _NoBA	75%	LD		
7	75_ MD _NoBA		MD		
8	25_ LD _NR_BA	25%	LD	NR	BA
9	25_ LD _R_BA		LD	R	
10	25_ MD _BA		MD	R	
11	50_ LD _NR_BA	50%	LD	NR	
12	50_ LD _R_BA		LD	R	
13	50_ MD _BA		MD	R	
14	75_ LD _NR_BA	75%	LD	NR	
15	75_ LD _R_BA		LD	R	
16	75_ MD _BA		MD	R	

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

5.5.4. Performance indicators

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

1. Delay per vehicle on the minor road (delay measured as the difference between the predicted and the actual travel time)
2. Delay per HDV on the major road

3. Delay per AV on the major road
4. Length of the queue on the minor road at the end of the simulation run (expressed in number of vehicles).

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.

5.6. 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.

5.6.1. Minor road delay

Figure 5.5 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 5.10 presents the percentage change in median delay between the different conditions, organized by the research questions.

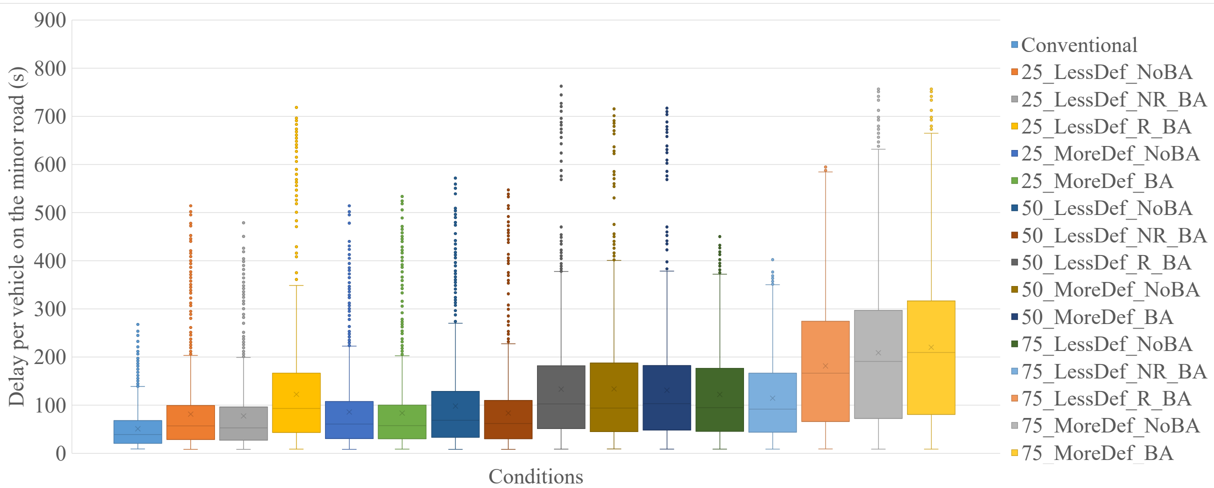

Figure 5.5: Boxplot distribution of delay per vehicle on the minor road for all conditions (R – Recognizable; NR – Not Recognizable; BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

Studying Table 5.10 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.

Boxplots for subsets of conditions are presented next for a better perspective. Figure 5.6 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.

Table 5.10: Percentage change in median delay between different conditions for vehicles on the minor road

	Condition	Change in median delay per vehicle (percentage)	
		MPR from 25% to 50%	MPR from 50% to 75%
Effect of Market Penetration Rate	NoBA, MD AVs	+54.97%	+103.17%
	NoBA, LD AVs	+20.39%	+38.15%
	BA, MD AVs	+79.44%	+102.92%
	BA, NR LD AVs	+17%	+48.29%
	BA, R LD AVs	+10.04%	+62.49%
	Recognizable compared to Not-Recognizable Less defensive AVs		
Effect of recognizability	BA, MPR 25%	+76.29%	
	BA, MPR 50%	+65.79%	
	BA, MPR 75%	+81.67%	
	More defensive compared to 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 compared to Not-Recognizable Less defensive AVs		
	BA, MPR 25%	+8.80%	
	BA, MPR 50%	+66.86%	
	BA, MPR 75%	+128.33%	
	More defensive AVs compared to Recognizable Less defensive AVs		
	BA, MPR 25%	-38.28%	
	BA, MPR 50%	+0.64%	
	BA, MPR 75%	+25.68%	
	With Behavioral Adaptation compared to Without Behavioral Adaptation Behavioral Adaptation compared to No Behavioral Adaptation		
Effect of considering behavioral adaptation	MD AVs MPR 25%	-5.19%	
	MD AVs MPR 50%	+9.77%	
	MD AVs MPR 75%	+9.64%	
	NR LD AVs MPR 25%	-7.38%	
	NR LD AVs MPR 50%	-9.98%	
	NR LD AVs MPR 75%	-3.37%	
	R LD AVs MPR 25%	+63.28%	
	R LD AVs MPR 50%	+49.24%	
	R LD 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

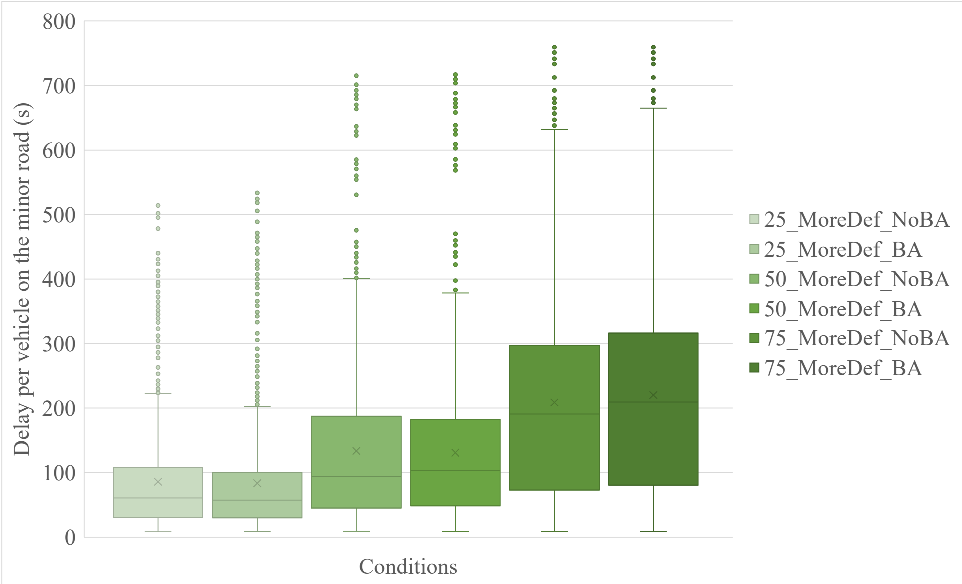

Figure 5.6: Boxplot of delay per vehicle on the minor road for More defensive AVs, with and without BA consideration, and for different penetration rates (BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; MoreDef – More defensive).

Figure 5.7 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.

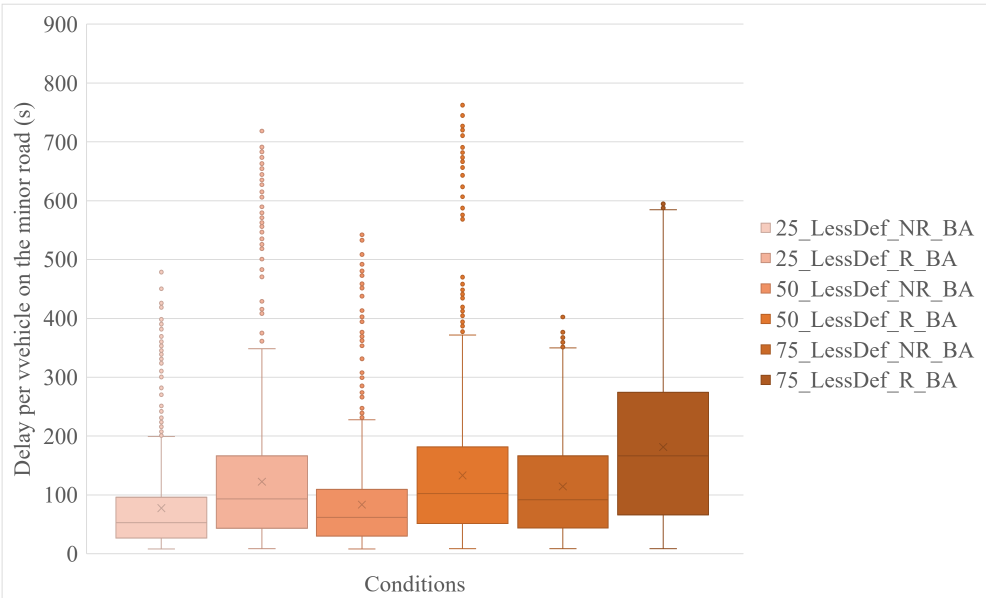

Figure 5.7: Boxplot of delay per vehicle on the minor road for Less defensive AVs condition and when considering behavioral adaptation, for recognizable vs not-recognizable AVs, and for different penetration rates (R – Recognizable; NR – Not Recognizable; BA – With Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

Figure 5.8 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).

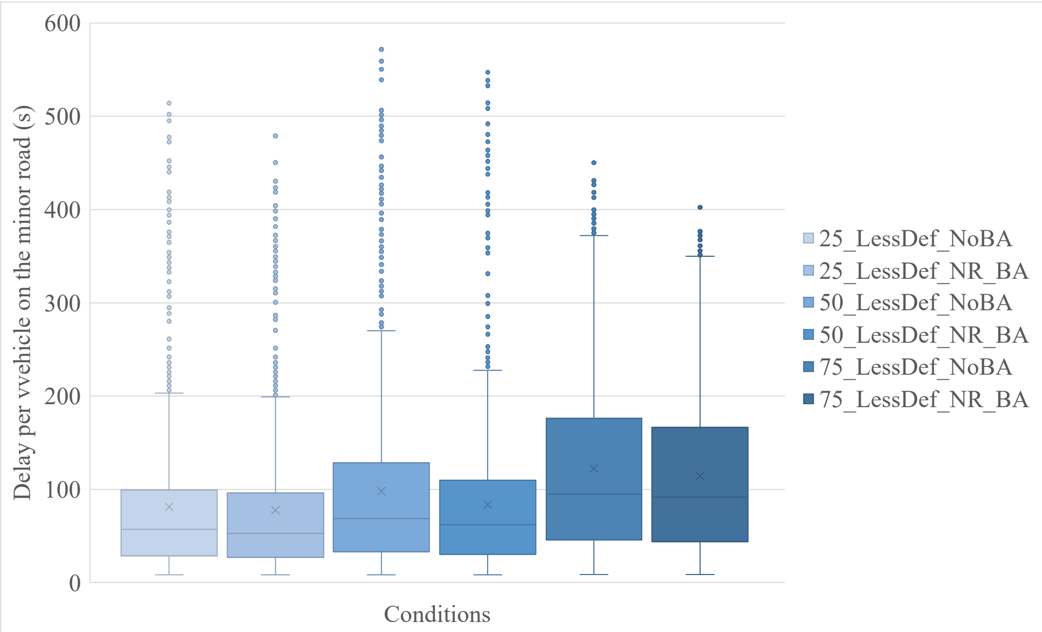

Figure 5.8: Boxplot of delay per vehicle on minor road for Less defensive AVs, with and without behavioral adaptation consideration when they are not-recognizable, and for different penetration rates (NR – Not Recognizable; BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

Figure 5.9 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.

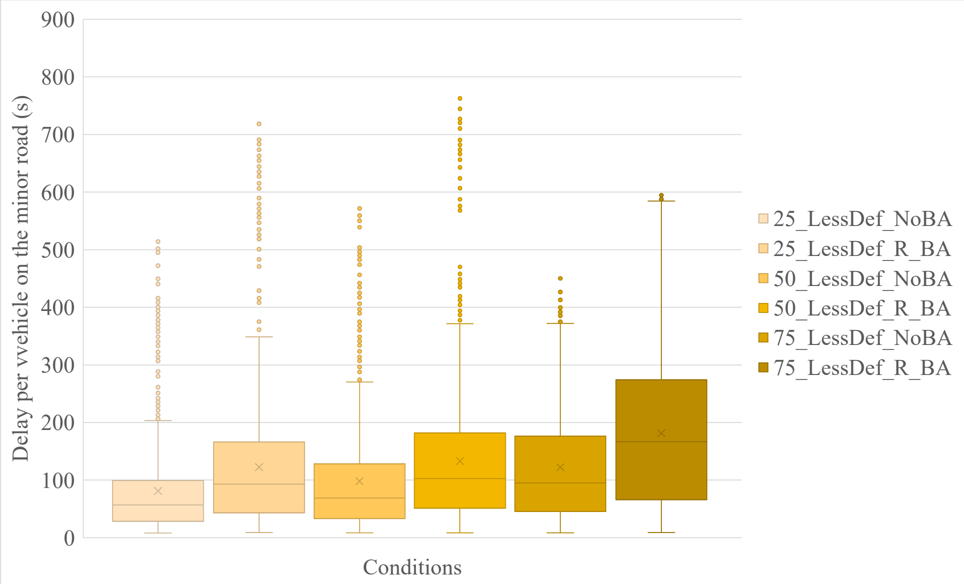

Figure 5.9: Boxplot of delay per vehicle on minor road for Less defensive AVs, with and without BA consideration when they are recognizable, and for different penetration rates (R – Recognizable; BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

5.6.2. Major road delay

Figure 5.10 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.

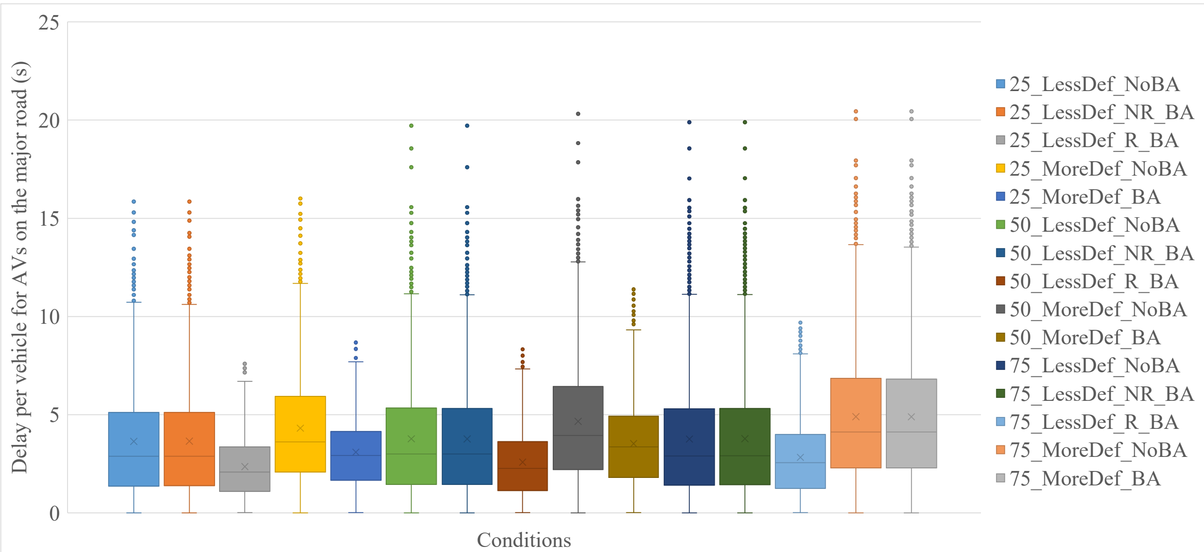

Figure 5.10: Boxplots of delay per vehicle for AVs on the major road (R – Recognizable; NR – Not Recognizable; BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

Figure 5.11 presents the boxplot distribution of the delay per vehicle on the major road for HDVs only. A clear contrast with AVs (Figure 5.10) 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.

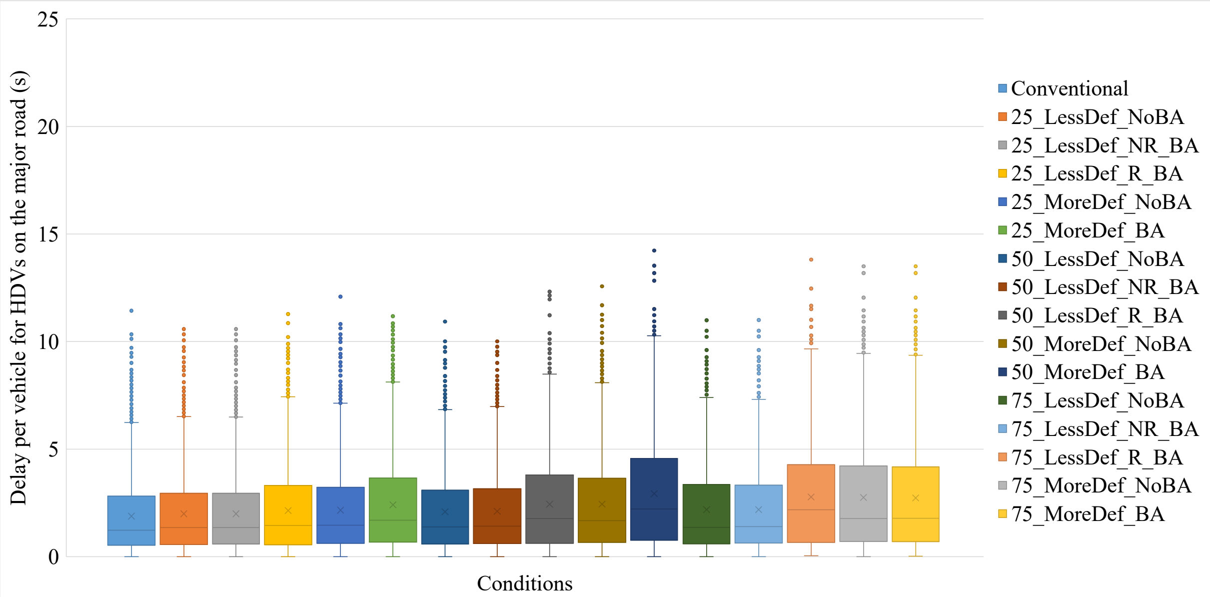

Figure 5.11: Boxplots of delay per vehicle for HDVs on the major road (R – Recognizable; NR – Not Recognizable; BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

Table 5.11 presents the percentage change in median delay for AVs and HDVs on the major road between the different simulation conditions.

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.

Table 5.11: 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	No BA, MD AVs	+9.14%	+15.07%	+4.57%	+5.95%
	BA, LD AVs	+4.17%	+2.96%	-3.50%	-2.16%
	BA, MD AVs	+15.07%	+30.59%	+22.62%	-19.37%
	BA, NR LD AVs	+3.81%	+4.80%	-3%	-1.41%
	BA, R LD AVs	+9.13%	+22.76%	+12.78%	+23.03%
		Recognizable compared to Non- recognizable 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 compared to 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 compared to Non-recognizable 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 compared to Recognizable 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 compared to without BA			
		AVs		HDVs	
Effect of considering behavioral adaptation	MD AVs MPR 25%	-19.11%		+16.44%	
	MD AVs MPR 50%	-14.72%		+32.14%	
	MD AVs MPR 75%	0%		+0.56%	
	NR LD AVs MPR 25%	+0.35%		+0.37%	
	NR LD AVs MPR 50%	0%		+2.16%	
	NR LD AVs MPR 75%	+0.52%		+2.94%	
	R LD AVs MPR 25%	-27.78%		+7.41%	
	R LD AVs MPR 50%	-24.33%		+28.06%	
	R LD AVs MPR 75%	-11.57%		+61.03%	

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

5.6.3. 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 5.12 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 5.12 presents the percentages differences in queue lengths between the different conditions organized by the research questions.

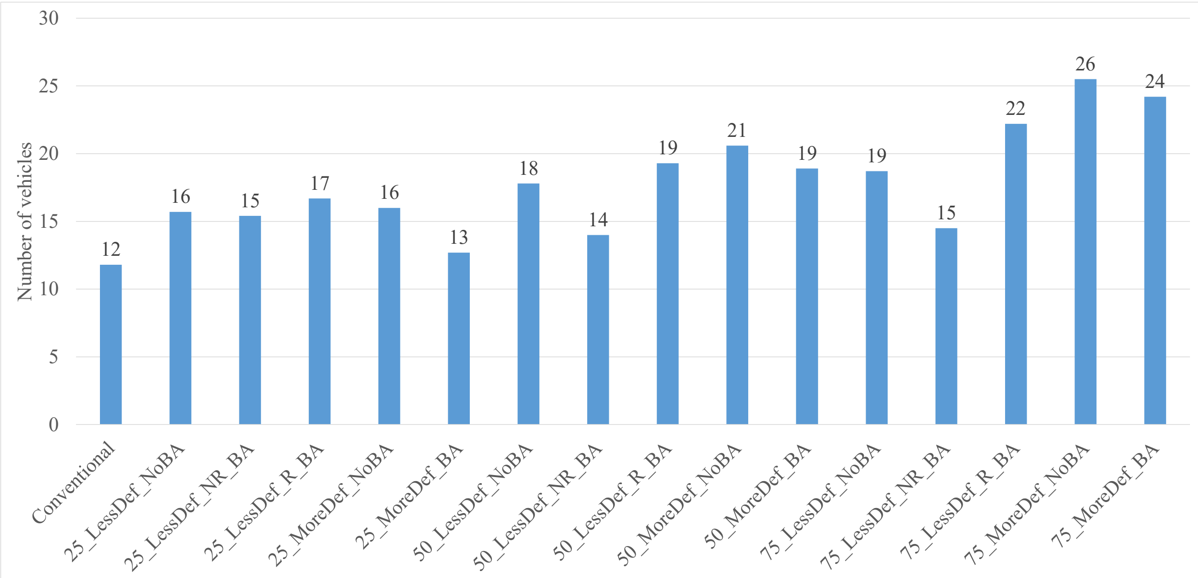

Figure 5.12: Number of vehicles remaining in queue on the minor road in different conditions at the end of each simulation run (R – Recognizable; NR – Not Recognizable; BA – With Behavioral Adaptation; NoBA – Without Behavioral Adaptation; LessDef – Less defensive; MoreDef – More defensive).

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 5.12: 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, MD AVs	+31.25%	+23.81%
	No BA, LD AVs	+12.50%	+5.56%
	BA, MD AVs	+46.15%	+26.32%
	BA, NR LD AVs	-7%	+7.14%
	BA, R LD AVs	11.76%	+15.79%
	Recognizable Less defensive AVs compared to Non-Recognizable Less defensive AVs		
Effect of recognizability	BA, MPR 25%	+13.33%	
	BA, MPR 50%	+35.71%	
	BA, MPR 75%	+46.67%	
	More defensive AVs compared to 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 compared to Non-Recognizable Less defensive AVs		
	BA, MPR 25%	-13.33%	
	BA, MPR 50%	+35.71%	
	BA, MPR 75%	+60.00%	
	More defensive AVs compared to Recognizable Less defensive AVs		
	BA, MPR 25%	-23.53%	
	BA, MPR 50%	0.00%	
	BA, MPR 75%	+9.09%	
	With Behavioral adaptation compared to without behavioral adaptation		
Effect of considering behavioral adaptation	MD AVs MPR 25%	-18.75%	
	MD AVs MPR 50%	-9.52%	
	MD AVs MPR 75%	-7.69%	
	NR LD AVs MPR 25%	-6.25%	
	NR LD AVs MPR 50%	-22.22%	
	NR LD AVs MPR 75%	-21.05%	
	R LD AVs MPR 25%	+6.25%	
	R LD AVs MPR 50%	+5.56%	
	R LD AVs MPR 75%	+15.79%	

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

5.7. 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.

5.7.1. 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.

5.7.2. 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.

5.7.3. 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.

5.7.4. 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.

5.8. 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.

5.9. 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.

5.10. Author contribution statement

Nagarjun Reddy: Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Visualization, Writing – Original Draft, Writing - Review & Editing

Narayana Raju: Conceptualization, Investigation, Methodology, Software, Visualization, Writing – Original Draft

Haneen Farah: Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Resources, Writing - Review & Editing

Serge Hoogendoorn: Supervision, Writing - Review & Editing

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5.12. Appendix

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 A-1.

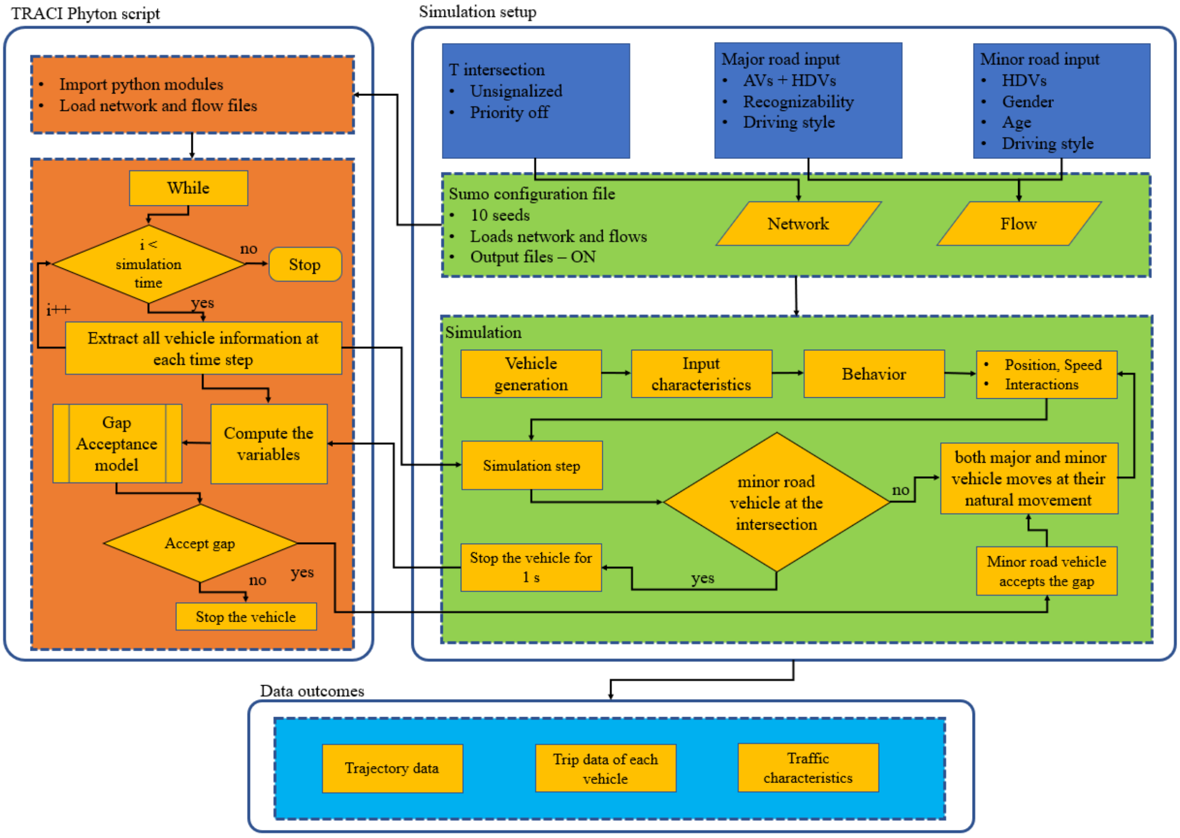

Figure A-1: Microscopic traffic simulation setup for modelling the gap acceptance behavior

Chapter 6:
Discussion And Conclusions

Chapter 6
Table of Contents

6. Discussion and conclusions

This chapter begins with the main Conclusions, which are primarily drawn from the research conducted in this thesis. However, these Conclusions go beyond merely presenting the direct findings. They are also informed by a discussion of the various results found in the individual chapters of the thesis, in combination with existing literature, and some degree of interpretation. Section 6.1 presents the main Conclusions, following which Section 6.2 discusses the answer to the main research question while performing a synthesis of the results, which forms the argumental basis for the main Conclusions. Additionally, Section 6.2 presents a tabular overview of all the individual results specifically from this thesis. Then, a reflection on the methodologies used in this study, and the limitations thereof are presented. Finally, potential implications or recommendations to various stakeholders are discussed, and avenues for future research are proposed.

6.1. The Main Conclusions

The main Conclusions from this research on the nature of behavioral adaptation of HDVs in – and their effects on – mixed traffic:

1. **Forward field of view**

There is a larger tendency for behavioral adaptions to occur in the forward field of view of AVs, for instance while merging in front of the AV in gap acceptance, or merging in front of the AV. This still recognizes that behavioral adaptation occurs in other behaviors and directions too, only that the extent could be smaller than in the forward field of view. There are also effects on traffic efficiency resulting from this. That is, the behavioral adaptations would result in noticeable traffic efficiency impacts particularly in situations where vehicles interact with each other in the forward field of view. For instance, this could be not only during gap acceptance and overtaking, but also for example during lane changing (in front of AVs). The effects on traffic efficiency can flow further upstream, but the cause of this would primarily be in interactions in the forward field of view.

2. **Effect of imitation**

When drivers do not recognize a vehicle as an AV, then the effect of imitation comes into play, where drivers tend to follow the driving behavior of vehicles around them. For instance, drivers tend to keep shorter headways if vehicles around them also keeps shorter headways, and vice versa. The effect of imitation points to human drivers potentially mimicking AVs driving behavior, when AVs are not recognizable. AVs keeping larger headways can cause human drivers also to keep larger headways. This could reduce the capacity of motorways for example. This means that how AVs are designed to drive affects not only their behavior and implications on traffic efficiency, but also makes other human drivers around them drive in a similar fashion when not recognizable, thus exacerbating the effects on traffic flow.

3. **Mechanism of trust**

If drivers recognize a vehicle as an AV, then the mechanism of trust comes into play, where the direction and extent of the behavioral adaptations depend on the level of trust drivers have in AVs. The mechanism of trust also highlights the importance of the design of AVs. If AVs are recognizable, the perception that human drivers have of AVs affects how human drivers drive. This perception would be a combination of the general trust human drivers would have in AVs (derived from previous knowledge, coverage in media, public information, etc.), in combination with how they perceive the AVs driving on the road. This is critical as human drivers could exhibit a range of behaviors from "exploiting" the safe driving behavior of AVs by driving more aggressively around AVs, or "being exploited" by the "less defensive" driving style of AVs. All this can have large consequences on traffic efficiency.

4. **Impact of behavioral adaptation on mixed traffic efficiency**

Mixed traffic factors affect human drivers' behaviors, which in turn has implications on traffic efficiency at a macroscopic level. Additionally, not considering behavioral adaptation of HDVs while predicting the traffic efficiency of mixed traffic could lead to inaccurate results. For example, not considering behavioral adaptations of HDVs in gap acceptance could lead to an underestimation of delay of minor road vehicles by about 75%.

In addition to these Conclusions, this thesis also found specific effects of mixed traffic aspects such as AV recognizability, driving style, penetration rates, and considering behavioral adaptation in microsimulation. These will briefly be discussed in the next section, and presented in the tabular overview later, but for a more specific results, the reader is referred to the individual chapters (the tabular overview later in this chapter helps to guide the reader to the right chapter for further study).

6.2. Synthesis of the results, and answering the main research question

What are the impacts of automated vehicles on the driving behavior of human-driven vehicles, and its resulting consequences on mixed traffic efficiency?

This section makes a synthesis of the different results found to see what kind of an overall picture do this dissertation's findings paint. Previous literature is cited where relevant, although in the individual chapters of this dissertation, a detailed reflection on literature has been made. This section also forms the argumentation basis for the Conclusions made in sub-section 6.1. The discussion in this section is organized by the individual studies.

On behavioral adaptation observed on real roads

The critical gaps and headways after overtaking were smaller when merging in front of a recognizable AV compared to an HDV. Moreover, with the provision of positive information, the critical gaps and the headways after overtaking reduced. The first takeaway from this field test provides the Conclusion that there exists a mechanism of trust when drivers make driving decisions. A default higher trust in AVs resulted in closer interactions. And the positive information further increased drivers' trust in AVs (measured by the increase in the reported trust levels), resulting in further closer interactions. In a field experiment by Zhao et al. (2020), it was also found that AV-believers maintained smaller time headways behind recognizable AVs. The effect of trust has also been shown with pedestrians, where pedestrians having greater trust in AVs have a higher intention to cross in front of AVs (Hagenzieker et al. (2020); Nuñez Velasco et al., 2019; Zhao et al., 2022). Another takeaway from the field test was the conclusion that drivers adapt their behaviors when interacting with AVs only when they are in the forward field of view of AVs, in other words, in front of AVs, because no change was observed when following behind the AV or while driving next to it during overtaking. The first driving simulator experiment allowed these two Conclusions to be tested.

On car-following behavior

Drivers had smaller desired speeds when following the lead vehicle that appeared as an AV, and when it had the AV driving style (for drivers having higher trust in AVs). This was not because drivers trusted AVs less, but because of the conservative driving behavior of the AV and drivers' inability to influence the AVs driving style when following it. This is explained by the finding that the larger the trust in AVs, the smaller was the jam spacing of drivers (also note that the safe time headways were larger when AV was recognizable). That is, drivers who trusted AVs more tended to keep a closer distance with the AV. Moreover, drivers having larger trust in AVs had smaller desired velocities when the lead vehicle had an AV driving style (more conservative driving style). Real world crash data also shows that most crashes between AVs and HDVs occurred when AV was at standstill while the HDV was driving straight behind the AV, thereby resulting in a rear-end collision (Xu et al., 2019). The findings of this dissertation could explain this as recognizable AVs could cause drivers to have smaller jam spacing and smaller safe time headways, particularly those having greater trust in AVs. Therefore, this underpins the mechanism of trust proposed earlier from the findings from the field test. However, this indicates that there is an effect of AV appearance on car-following behavior. But the earlier field test proposed that there is only behavioral adaptation in the forward field of view. Contrastingly, the driving simulator experiment showed closer maneuvers also while driving behind an AV. This can be explained as follows. In the field test, the test vehicle had the same driving style between the AV and HDV scenarios (in practice the vehicle was driven by the same human driver), and a human safety driver was always present inside. In the driving simulator, however, AVs and HDVs had different driving behaviors. The difference between safe time gap of AV HDV scenario and HDV HDV scenario, was about half as small as the difference between AV AV scenario and HDV HDV scenario (the HDV HDV scenario having larger values for both cases). Therefore, this suggests that driving style differences were perceived. The driving simulator experiment also had a larger sample size (47) compared to the field test (18). So, the finding of the driving simulator experiment (closer interactions when car-following) carries significant additional importance. In existing literature, however, there is evidence of behavioral adaptation both in gap acceptance (Trende et al., 2019), lane changing (S. Lee et al., 2018; S. Y. Lee & Oh, 2017; Razmi Rad et al., 2021) as well as in car following (Mahdinia et al., 2021; Rahmati et al., 2019; Zhao et al., 2020). We could consider lane changing to also be a forward field of view interaction as drivers merge in front of another vehicle. In any case, there is evidence also in literature for behavioral adaptations to occur both in the forward field of view as well as when driving behind the AV. However, I do not propose to reject the forward field of view Conclusion. It could still be possible that the impact of behavioral adaptation is greater in the forward field of view than when interacting from other directions. What both the field test and this driving simulator experiment point to is that there is a mechanism of trust in AVs that impacts the level of behavioral adaptation.

On gap acceptance behavior

Neither the AV appearance nor the AV driving style independently affected drivers' gap acceptance behavior, but only when combined. This supports the Conclusion that when AVs were not recognizable, there is an effect of imitation in human drivers, which nudges them to follow the behavior of drivers around them. Drivers were found to drive less defensively when AVs that were not recognizable drove less defensively, and vice versa. In the driving simulator experiment by Gouy et al. (2014), the authors found that drivers reduced their time headways when driving next to non-recognizable AV platoons that also had smaller time headways, therefore also pointing towards an imitation behavior. When AVs were recognizable, however, the experiment results suggested a mechanism of trust. When recognizable AVs drove more defensively, drivers drove less defensively, and when recognizable AVs drove less defensively, drivers drove more defensively (Hulse et al., 2018). The findings in Schoenmakers et al. (2021) also support this, where they found that drivers drove with significantly smaller time headways when driving in proximity of AV platoons. In the first driving simulator experiment where AVs had a more conservative behavior than HDVs, higher trust in AVs resulted in smaller jam spacing. This supports the mechanism of trust Conclusion. Current literature also highlights the importance of risk perception with respect to AVs (Hulse et al., 2018). The concepts of trust and risk perception are closely related, as found in Zhang et al. (2019) where perceived risk had a negative effect on the acceptance of AVs through trust.

There is additional evidence from the first driving simulator experiment for the effect of imitation. If the effect of imitation mechanism is valid, then compared to HDV HDV (Appearance, Driving style), drivers must drive more conservative in the HDV AV scenario (as AV driving style was more conservative than HDV driving style). Compared to the HDV HDV scenario, drivers had a larger jam spacing, almost the same safe time headway, and smaller max acceleration in the HDV AV scenario. This points towards more conservative driving, thus supporting the effect of imitation mechanism. And if the mechanism of trustis valid, then drivers must drive more aggressive in the AV AV scenario. Compared to the HDV HDV scenario, drivers had a smaller jam spacing and smaller safe time gap in the AV AV scenario. This points towards more risky driving, thus supporting the mechanism of trust.

To conclude, we can say that firstly, there is a larger tendency for behavioral adaptions to occur in the forward field of view of AVs. This still recognizes that behavioral adaptation occurs in other behaviors and directions too, only that the extent could be smaller than in the forward field of view. Secondly, if drivers do not recognize a vehicle as an AV, then the effect of imitation comes into play, where drivers tend to follow the driving behavior of vehicles around them. Thirdly, if drivers recognize a vehicle as an AV, then the mechanism of trust comes into play, where the direction and extent of the behavioral adaptations depend on the level of trust drivers have in AVs.

On the impact on traffic efficiency

In general, AVs deteriorated traffic efficiency because of larger time headways than HDVs. Along the same lines, more defensive AVs have larger time headways and hence can cause greater delays to minor road vehicles. It was also found that not considering behavioral adaptation could result in a large underestimation of the measured delays for minor road vehicles. While these were the effects on traffic efficiency, I did not study the impacts on traffic safety, which could have different implications.

With the results of the microsimulation study, two key aspects must be kept in mind. First, that it was a priority intersection, which means that the major road always had priority. Therefore, the delays were almost completely experienced only by minor road vehicles. If it was not a priority intersection, then delays would have also been experienced more by traffic on the major road, and with larger AV time headways, there could be significant spillbacks on the major road. Second, we assumed that traffic arrives in platoons that are binomially distributed and in a semi-congested traffic volume. If the major road traffic volume would be very low, there would be negligible delays. But if the major road were more congested, then the minor road vehicles would face very large delays, and in the real world, could even lead to forced entries due to the impossibility of finding a gap (this would apply also if there was a uniform distribution instead of a binomial distribution of major road vehicles).

These findings show that AVs could deteriorate traffic efficiency at intersections, causing more delays and also longer queues building up on the minor road. This could have significant impacts especially where the road space is limited, leading to blocking the upstream road network/ intersections. The findings also show that behavioral adaptation must be considered when making any models or simulations or prediction studies on the impact of AVs on mixed traffic to gain an accurate understanding of future traffic situations.

There are also traffic efficiency effects resulting from the Conclusions discussed before. The forward field of view Conclusion implies that traffic efficiency implications could also primarily occur in the forward field of view of AVs. This could be not only during gap acceptance and overtaking, but also for example during lane changing (in front of AVs). Lane changes particularly can affect traffic flow efficiency on motorways. The effect of imitation Conclusion also points to human drivers potentially mimicking AVs driving behavior, when AVs are not recognizable. This means that how AVs are designed to drive affects not only their behavior and implications on traffic efficiency, but also makes other human drivers around them drive in a similar fashion when not recognizable, thus exacerbating the effects on traffic flow. AVs keeping larger headways can cause human drivers also to keep larger headways. This could reduce the capacity of motorways for example. The mechanism of trust also highlights the importance the design of AVs. If AVs are recognizable, the perception that human drivers have of AVs affects how human drivers drive. This perception would be a combination of the general trust human drivers would have on AVs (derived from previous knowledge, coverage in media, public information, etc.), in combination with how they perceive the AVs driving on the road. This is critical as human drivers could exhibit a range of behaviors from “exploiting” the safe driving behavior of AVs by driving more aggressively around AVs or “being exploited” by the “less defensive” driving style of AVs. All this can have large consequences on traffic efficiency.

A compilation of all the findings made across the different studies is presented in Table 6.1 and Table 6.2. It is an overview of all the behavioral adaptations and impacts observed as part of this dissertation. The tables only present the effects that resulted in a (significant) change in the indicators, only for mixed traffic specific factors. The factors did not have any significant effect on the other indicators. The complete list of factors considered in this dissertation were: Mixed traffic specific factors (AV appearance, AV driving style, trust in AVs, AV penetration rate, considering behavioral adaptation), general factors (Driver age, driver gender, driver driving style). The complete list of indicators investigated were: Car-following (Jam spacing, Desired velocity, Safe time headway, Maximum acceleration, Comfortable deceleration), Gap acceptance (Accepted gap size, Critical gap, probability of accepting a gap), Overtaking (Headway after overtaking, Lateral distance while overtaking), Traffic efficiency at priority T intersection(Delay per vehicle on minor road, Delay per vehicle on major road, Queue length).The limitations and reflections on the methods used in this research of this dissertation is discussed in the next section.

Table 6.1: Overview of the effects of mixed traffic factors on human driver car-following and overtaking behavior

Behavior	Factor	Indicator	Effect		Study	Chapter
CAR-FOLLOWING	**AV appearance**	**Desired velocity**	↓	Smaller desired velocity when following vehicle appearing as AV compared to HDV.	Modelling using empirical data	3
		Safe time headway	↓	Smaller safe time headway when appearance is AV compared to HDV.		
		Jam spacing distance	↓	Smaller jam spacing distance when following vehicle appearing as AV compared to HDV.		
			↓	When following vehicle appearing as AV, jam spacing further reduces when drivers have higher trust in AVs		
		Comfortable deceleration	↑	When following vehicle appearing as AV, larger comfortable deceleration when drivers have higher trust in AVs		
	AV driving style	**Desired velocity**	↓	When driving style is AV, desired velocity smaller for drivers having higher trust in AVs.		
	Trust in AVs	**Desired velocity**	↓	When driving style is AV, desired velocity smaller for drivers having higher trust in AVs.		
		Jam spacing distance	↓	When following vehicle appearing as AV, jam spacing further reduces when drivers have higher trust in AVs		
		Comfortable deceleration	↑	When following vehicle appearing as AV, larger comfortable deceleration when drivers have higher trust in AVs		
OVERTAKING	**AV appearance**	**Headway after overtaking**	↓	Smaller headway after overtaking a recognisable AV compared to HDV.	Controlled field test	2

Table 6.2: Overview of the effects of mixed traffic factors on human driver gap acceptance behavior and traffic efficiency

Behavior	Factor	Indicator	Effect	Study	Chapter
GAP ACCEPTANCE	**AV appearance**	**Accepted gap size**	↑ Largest accepted gap when AVs were recognizable, with less defensive driving style, and merging in front of an AV.	Driving simulator	4
		Critical gap	↓ Smaller critical gap when appearance is AV compared to HDV.	Controlled field test	2
			↓ When AVs are non-recognizable, critical gaps significantly smaller when AVs were less defensive compared to more defensive.	Driving simulator	4
			↑ But when recognizable, critical gaps significantly larger when AVs were less defensive compared to more defensive (when merging in front of AV).		
	AV driving style	**Accepted gap size**	↑ Largest accepted gap when AVs were recognizable, with less defensive driving style, and merging in front of an AV.		
		Critical gap	↑ When AVs are recognizable, critical gaps significantly larger when AVs were less defensive compared to more defensive (when merging in front of AV).		
			↓ When AVs are non-recognizable, critical gaps significantly smaller when AVs were less defensive compared to more defensive.		
	Trust in AVs	**Critical gap**	↓ Provision of positive information on AVs (increasing trust) reduces critical gap further.	Controlled field test	2
TRAFFIC EFFICIENCY AT PRIORITY T-INTERSECTION	**AV appearance**	**Delay for minor road vehicles**	↑ When AVs were less defensive, larger delays for minor road vehicles when AVs were recognizable compared to being non-recognizable.	Microsimulation	5
	AV driving style	**Delay for minor road vehicles**	↑ Increase in delay with AV penetration rate is larger when the major road has More defensive AVs compared to when it has Less defensive AVs.		
			↑ At larger penetration rates, delay for minor road vehicles is larger when AVs are more defensive as compared to when AVs are recognizable and less defensive.		
		Queue length	↑ Longest queue was observed in 75% AV penetration rate traffic with more defensive AVs (behavioral adaptation not considered); and shortest queue length was observed in conventional (fully HDV) traffic.		
	AV penetration rate	**Delay for minor road vehicles**	↑ Increase in AV penetration rate increased delay for minor road vehicles.		
		Queue length	↑ Longest queue was observed in 75% AV penetration rate traffic with more defensive AVs (behavioral adaptation not considered); and shortest queue length was observed in conventional (fully HDV) traffic.		
	Considering Behavioral Adaptation	**Delay for minor road vehicles**	↑ In less defensive AV traffic, considering behavioral adaptation results in an increase in delay per minor road vehicle by up to 75% (at 75% penetration rate).		

6.3. Reflection on methodology

This dissertation fused a range of different methods to address the research questions. These ranged from a controlled field test, driving simulator experiments, modelling, calibration, and microsimulation. Each of these methods required several decisions to be made. And consequently, the methods had their own specific limitations. These limitations, on one hand, had implications on the validity of the results of the executed studies, and on the other hand also guide future studies that result from, or take inspiration from this dissertation. The exact limitations of the various studied conducted are already discussed in the relevant chapters. This section focuses more on some key learnings from the different studies that were conducted.

One important insight is being conscious of what exactly is being measured. For example, in the driving simulator experiment to study gap acceptance, drivers made gap acceptance decisions at the intersections. However, they had driven on the route prior to the intersections where they had experienced the specific traffic conditions. Therefore, their prior experience on the route would influence their behavior at the intersections, in addition to the specific conditions at the intersections. Therefore, there is a combination of the “carry-over effect” and the effect of the condition encountered at the experiment. It is important to be aware of such aspects to not wrongly attribute the observed behavior to solely the immediate surroundings. Additionally, it is important to consider learning effects in experiments. Participants change their behavior between scenarios not only due to the scenario conditions but also due to being more familiar and comfortable in the experiment set up. We accounted for this by randomizing the scenario order. But there could also be other ways to take into account, especially if a specific order of scenarios is demanded, such as by including the cumulative number of kilometers driven as a variable during modelling. Also, it should be noted whether it is short term or long term effects that are being measured. This dissertation measured behavioral adaptations in the short term only. Long term effects studies would have to study participants over a longer period of time, which can have its own challenges. Adding to the point of being aware of what is being measured, the same applies to the measurement of trust. In this research, we measured trust in AVs. This primarily meant that participants in the experiment were explicitly asked to rate their trust in AVs. However, trust is a latent variable and difficult to measure. It is also prone to subjectivity in understanding of the object under assessment, and in the interpretation of the term “trust”, and in the self-assessment of the individual’s extent of trust. Therefore, the measurement of trust must be paid attention to. Another aspect that ties to this is risk perception. Lower trust in the AVs would lead to higher perceived risk of AVs, and vice versa. The definitional difference between trust and risk perception, and their relationship with each other, is still under debate (He et al., 2022; Nordhoff et al., 2021; Pyrialakou et al., 2020; Xu et al., 2018). As far as this dissertation is concerned, I did not differentiate between these two concepts. When these terms were used in this research, they point to the same concept.

This dissertation used a combination of different data collection methods, such as the field test and driving simulator to study similar behaviors (gap acceptance and car-following). This combination of methods not only enriches the findings with new insights, but also allows the possibility to make a deeper analysis of the underlying mechanisms contributing to the behavioral adaptations (such as the forward field of view, effect of imitation, and mechanism of trust). Field tests offer more valid results, while driving simulators offer greater flexibility to test different conditions. A combination is therefore more powerful than a single method. Another critical aspect is the definitions of vehicle behaviors. This is not trivial and vehicle behaviors must be defined based on the goal set for the study. If the goal is to implement real life situation, then the behaviors of vehicles must be sourced from valid data of currently operating vehicles (AVs and HDVs). If the goal is more to test the effects of different factors such as driving style, then the requirement to base it on current real-life data is less important, but it is still important that it does not deviate too much from reality, if the results are to be practically useful. Also, defining vehicle behaviors should consider going beyond the desired speed and desired time headway differences. For instance, differences in steering behavior, lane changing behavior, even gap acceptance behavior can improve the realism and differences of the driving behaviors between AVs and HDVs.

The same applies to how AV appearance is defined. Conscious decisions must be made on firstly, the physical appearance of AVs in experiments (should it represent reality or test different appearance designs, similar to driving behavior); and secondly, on whether participants are made aware prior to the experiment on how to recognize an AV. In the experiments conducted in this dissertation, the effect of recognizing a vehicle as AV was tested. Hence, participants were aware of how an AV looked like. This allowed to test the effect of knowing which vehicle is an AV and which is not. The advantage was that it was known that participants could recognize an AV. What could not be tested however was whether a certain appearance design would allow participants to identify a vehicle as an AV without any other information.

As for participants, the sample size and diversity of participants is also not trivial. This dissertation, and many previous literature, has found that different groups of people (for example: age, gender, driving style, knowledge of AVs) have different driving behaviors. It is important therefore to have a representative sample and to collect and report on the demographics and other personal attributes (driving style, knowledge and experience of AVs, etc.) of participants.

Another aspect is the time pressure in research experiments. In real life, drivers are generally in a rush, especially during peak hours. Their driving behaviors, and any potential behavioral adaptations are different from the conditions present in research experiments where people tend to be more relaxed. To have more realistic conditions, we adopted a method in the third driving simulator experiment where we displayed a message sign during the middle of the experiment that said that the participant is a few minutes late. Other such methods include conditioning the compensation provided on finishing the experiment in time, or other rewards or punishments for being on time versus being late, respectively. Caution must be adopted to not affect the natural driving behavior of the drivers while employing these methods.

Concerning the analysis of results, for experiments with repeated measures, that is, where the same set of participants drive different scenarios, estimating mixed models is a good approach because it allows a more accurate insight into the impacts of various factors. Mixed models correct for repeated measures. Therefore, it is not sufficient to base insights only from the resulting descriptive statistics, if a more accurate investigation is needed. As for car-following model estimation, a “complete trajectory” is recommended to be adopted in the experiment set up. This ensures that all different types of driving regimes are covered, and hence the resulting models will be more valid and generalizable. Moreover, decisions of estimation and calibration must be done with care, and best practices for estimations should be adopted. The first driving simulator experiment describes more about a complete trajectory and also best estimation practices for car-following models.

Another aspect to consider is that transferring results from driving simulator to real world is not so easy and direct. As I conducted a controlled field test and a driving simulator experiment and measured the same variables (critical gap and car-following), I found that on one hand, there were similarities (the direction of effects on critical gap), but there were differences on the magnitude of effects. On the other hand, there can also be complete differences too (for example car-following behavior, but this was most likely due to differences in experiment set up). The focus of this research was more to study different aspects affecting HDV behavior and not to compare results of a field test with those of a driving simulator. Hence, the exact same set up was not done. In general, effects in real life driving could have similar directions as those measured in driving simulators, but the magnitude could be different. Finally, there needs to be a difference made between statistical significance and practical significance. Statistical significance does not necessarily indicate practical significance, and not being statistically significant does not mean also not being practical significant. For example, additional delays caused due to behavioral adaptation in gap acceptance may not be statistically significant. But in practice, if it causes effects such as spillback and blocks the upstream road network, it could still be practically significant.

6.4. Practical implications

This section presents potential implications of the results of this research to different stakeholders.

Drivers of manual vehicles

Drivers of manual vehicles are directly affected by mixed traffic. Firstly, they will soon be able to distinguish AVs from HDVs, unless AVs are completely non-recognizable. If AVs have a distinct driving style, HDVs will adopt their behavior accordingly. They may find themselves driving more cautiously if AVs are less defensive. This would affect traffic efficiency, causing drivers to experience more delays. On the other hand, it could be that traffic safety would be improved due to drivers maintaining larger distances from AVs. It may also occur that because of more delays, drivers start driving less cautiously again to compensate for their delays. If AVs drive defensively however, then drivers make closer maneuvers, thereby improving traffic efficiency, potentially at the cost of traffic safety. Non-recognizable AVs would have an inverse effect, where drivers would mimic the AV driving style.

Automated vehicle users

Considering a basic level of AV such as Adaptive Cruise Control (ACC), short (less defensive) headway settings in a recognizable AVs causes other human drivers to perform maneuvers further away from the AV. This may encourage AV users to keep such short settings as their individual travel experience could become better. This could suggest the exploitation of other (HDV) traffic by AV users. However, this could be a temporary effect because human drivers adapt their behavior with time when becoming more familiar with and accustomed to less defensive AVs, and therefore can once again drive as they do normally or even more aggressively. On the contrary, when less defensive AVs are non-recognizable, other human drivers perform more aggressive maneuvers. This could lead to the exploitation of AVs by other human drivers (unintentionally). In essence, it appears that AV users could prefer AVs that are recognizable and keep smaller headway settings. This combination would best serve their needs.

Road authorities

Road authorities are increasingly considering Infrastructure to Vehicle (I2V) communication. Such information could not only include the state of the road downstream, but also explicit instructions for the AV to drive in a certain way. When authorities provide such instructions to AVs in mixed traffic, they need to consider the possible behavioral adaptations. For instance, asking (recognizable) AVs to decrease their time headway could cause HDVs to drive in a way that can even decrease traffic efficiency. On the other hand, asking (recognizable) AVs to increase their time headway may cause other HDVs to perform risky maneuvers. Examples of I2V situations where this could be relevant are the provision of Variable Speed Limits to AVs upstream, and the provision of time to green information from intelligent intersection controllers to AVs.

As found in this dissertation, at priority intersections, AVs can result in larger delays for minor road vehicles. This could mean larger spill back effects, affecting other parts of road network. Larger time headways of AVs could also mean reduction of capacity on also motorways and general road network. Therefore, road authorities must be conscious of such effects. At the same time, this is only traffic efficiency and not safety, which must be given paramount importance.

It must also be considered whether the behavioral adaptations observed and the impacts on traffic efficiency measured are meaningful enough to adopt any countermeasures. Making road infrastructural changes is expensive and more long term. With rapidly changing AV technology, care must be taken to align long term road infrastructure decisions with the expected vehicle technology and behavior.

Driving license and vehicle licensing authorities

Driving license authorities are advised to help human drivers become more aware of potential behavioral adaptations they undergo, and to train them on how to drive in the presence of AVs. Drivers could be trained to try becoming more aware of driving consciously using existing techniques, for example defensive driving, specifically in the context of mixed traffic conditions. Additionally, being more conscious of aspects of effect of imitation and mechanism of trust would make drivers make more aware decisions.

Vehicle licensing authorities are advised to consider whether AVs should be recognizable. In either way, there are implications on traffic efficiency. Also, it may be useful to develop a defined range of permitted settings for AV users. For example, users of an ACC would be allowed to choose a time gap between 1.5 and 3.5 s only, not smaller and not larger. This can allow for more homogeneity in AV behavior. Defining lower and upper limits also allows car manufacturers to still offer their customized options to their users.

AV car manufacturers

AV car manufacturers desire to have a comfortable experience for their users, while ensuring safety. While they satisfy the legal requirements, car manufacturers still have significant room to make decisions on the appearance and driving style of AVs. They must investigate the implications of such decisions and including the implications of having various driving settings. Specifically, how would the users respond and use these settings, and the resulting implications on the surrounding traffic. Also, car manufacturers could help make their users aware of the consequence of using their cars and keeping certain settings. If other drivers perceive AVs as defensive and safe, then drivers might drive more aggressively or make closer maneuvers in front of AVs. Therefore, vehicle manufacturers could consider monitoring the attention of AV drivers more frequently, so they are prepared to take over if necessary. External Human-Machine Interfaces could also be a way to control risky cut-ins by other HDVs, such as by having a visible indication feature to warn the other human drivers that the AV's current headway in insufficient to make a safe lane change in front of it.

Ideally, a close collaboration between all stakeholders is required to ensure safe and comfortable driving conditions.

6.5. Avenues for future research

To further continue research in this topic of behavioral adaptation and implications on traffic performance, there are several possible research directions. The individual chapters of this dissertation already provide avenues for future research. Also, section 3 of this chapter provided a reflection on methodology that would be of assistance to future research by highlighting some key aspects to consider while investigating this topic. This section provides some further key global additions based on the main research findings of this dissertation.

Future research in this area is encouraged to further investigate and specify the Conclusions made in this thesis: forward field of view, effect of imitation, mechanism of trust, and impact of behavioral adaptation on mixed traffic efficiency. As for the forward field of view, it is important to define what behaviors exactly constitute the forward field of view (such as lane changing in front of AV, gap acceptance, merging). Then, it is interesting to investigate how the behavioral adaptations of different driving maneuvers within the forward field of view compare with each other in terms of their magnitudes and directions. Another interesting question is whether behavioral adaptation is always present in the forward field of view or are there conditions for it to occur. Finally, does the existence of behavioral adaptation in the forward field of view always imply behavioral adaptation in other directions. If not, then research should be done into what conditions or characteristics make the forward field of view more prone to behavioral adaptations.

As for effect of imitation, firstly, the reasons for imitation must be investigated and well understood. Also, what type of behaviors are more prone to being complied with is an interesting topic. Moreover, to what extent does imitation occur, and if there are any limits to imitation is important. Finally, it should be tested whether imitation is different in different road situations or conditions.

As for mechanism of trust, there are increasingly more methods to measure trust, which is not a trivial variable to measure. First, these measures must be investigated and further developed. These are not directly measurable variables, hence future research must understand these better, also by taking insights from other fields such as aviation. Also, more elaborately characterizing the effect of trust on behavior is important to understand their effect better. Moreover, future research could conduct sensitivity analysis of trust effect on the behavior. For example, do their effects on behavior have a limit; or does a change in trust have a linear effect on behavior. Another important aspect to research is to test and characterize the two components defined in this dissertation: 1) predisposed trust and 2) real time trust level changes. It would be interesting to see how they compare with each other. And also, how do these vary in different road situations and conditions. Finally, the effects of different types of information on trust is also a useful research topic.

In addition to the above-mentioned topics, the overarching question of how these three Conclusions relate to and influence each other would be a crucial topic to research. Also, there could also be other factors that may be relevant such as sense of urgency. In any case, future studies are encouraged to report and interpret their results using these proposed concepts.

More investigation for evidence of behavioral adaptation and the magnitude and direction of the effects is required as the current research is still at a nascent stage. Also, more simulation studies on the effect on traffic efficiency, considering behavioral adaptation is required. One key finding in this dissertation was that the less defensive driving style of recognizable AVs induces defensive driving in human drivers. This less defensive driving style of AVs can improve traffic efficiency. However, the defensive driving induced in other human drivers could compensate or cancel out any positive benefits brought by the AVs. Future research can delve into this area and study how the ratio of less defensive and more defensive AVs affects behavioral adaptation, and the resulting implications on traffic efficiency. Effects on traffic efficiency including behavioral adaptation should be studied in other road situations such as straight road driving (motorways) and roundabouts. It would also be interesting to study the effects on other road users such as cyclists and pedestrians.

The impacts on other performance indicators must be investigated, particularly traffic safety. Behavioral adaptations could have direct implications on traffic safety, particularly in critical maneuvers such as lane changing and gap acceptance. Existing measures of traffic could be used to get insights into this. As there is not much publicly available data for these kind of studies, data collection efforts must increase, and even if in controlled environments, indicators such as surrogate safety measures could lead to gaining insights into traffic safety.

One important aspect is that the effect of considering or not considering behavioral adaptation needs to be further investigated. This has not been done yet to the best of my knowledge, except in this dissertation. Also, the impacts on other performance indicators such as traffic safety, energy, and emissions could be investigated in future research.

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About the Author

Nagarjun Reddy was born in India in 1995. He earned a Bachelor of Engineering degree in Civil Engineering from R.V. College of Engineering, Bangalore, in 2017. He subsequently pursued a Master's degree in Civil Engineering (Transport & Planning) at Delft University of Technology, completing it in 2019 with a thesis on infrastructure requirements for improving the performance of lane assistance systems. During his Master's program, he served on the board of Dispuut Verkeer, the student association for transport, infrastructure, and logistics.

In 2019, Nagarjun began his doctoral studies in the Department of Transport and Planning at Delft University of Technology. His research is part of the SAMEN project, which focuses on the interactions between human-driven and automated vehicles in mixed traffic. His work includes the design and execution of driving simulator and field experiments to study these interactions, in collaboration with project partners from academia, government, and industry. During his PhD, Nagarjun has contributed to academic publications, participated in international conferences, and supervised student projects related to his research. He was also a member of the PhD Council at the TRAIL Research School, where he represented doctoral candidates and contributed to academic and professional activities.

Nagarjun recently began working as an advisor at Arane Adviseurs, contributing to projects related to traffic and transport systems. He is also the founder of The Synergy Hub, a startup whose vision is to help build collaboration in organizations.

List of publications

1. Reddy, N., Hoogendoorn, S. P., & Farah, H. (2022). *How do the recognizability and driving styles of automated vehicles affect human drivers' gap acceptance at T-Intersections?* Transportation Research Part F: Traffic Psychology and Behaviour, 90, 451–465. https://doi.org/10.1016/J.TRF.2022.09.018
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3. Soni, S., Reddy, N., Tsapi, A., van Arem, B., & Farah, H. (2022). *Behavioral adaptations of human drivers interacting with automated vehicles.* Transportation Research Part F: Traffic Psychology and Behaviour, 86(February), 48–64. https://doi.org/10.1016/j.trf.2022.02.002
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List of conferences

1. Reddy, N., Raju, N., Farah, H. & Hoogendoorn, S. P. (2024, September 2–4). *Incorporating behavioral adaptation of human drivers in predicting traffic efficiency of mixed traffic: A case study of priority T-intersections*. Presented at the Conference in Emerging Technologies in Transportation Systems (TRC-30), Heraklion, Greece.
2. Reddy, N., Hoogendoorn, S. P., & Farah, H. (2023, October 31). *Human driving behavior in mixed traffic at motorway on-ramps, signalized provincial road intersections, and car following behind leader: A driving simulator experiment*. Presented at the TRAIL PhD Congress, Utrecht, Netherlands.
3. Reddy, N., Hoogendoorn, S. P., & Farah, H. (2023, October 26–27). *Incorporating behavioral adaptation of human drivers in predicting traffic efficiency of mixed traffic: A case study of priority T-intersections*. Presented at the International Cooperation on Theories and Concepts in Traffic Safety (ICTCT), Catania, Italy.
4. Reddy, N., Hoogendoorn, S. P., & Farah, H. (2022, September 20). *Car-following and lane-changing behavior of human drivers in mixed traffic: A driving simulator experiment*. Presented at the TRAIL PhD Congress, Utrecht, Netherlands.
5. Reddy, N., Wiersma, J., Farah, H. (2022, August 22–24). *Would human drivers change their behavior when driving alongside automated vehicles that are connected to variable speed limit signs on motorways?* Poster presented at the International Conference on Human Interaction and Emerging Technologies, Nice, France.
6. Reddy, N., Hoogendoorn, S. P., & Farah, H. (2022, June 8–10). *Gap acceptance behavior at priority intersections in mixed—Human-driven and automated—Vehicle traffic*. Presented at the Road Safety and Simulation Conference, Athens, Greece.
7. Reddy, N., Farah, H., Huang, Y., Dekker, T., & van Arem, B. (2022, June). *Road infrastructure requirements for improved performance of lane assistance systems*. Presented at the International Symposium for Highway Geometric Design, Amsterdam, Netherlands.
8. Nagarjun Reddy. (2020, May 26–28). *How will we drive in the future? Modelling human driving behaviour in mixed traffic*. Presented at the Challenges of Automated Vehicles and Traffic conference by Széchenyi István University, Online.
9. Reddy, N., Farah, H., Huang, Y., Dekker, T., & van Arem, B. (2020, January 12–16). *Road infrastructure requirements for improved performance of lane assistance systems*. Poster presented at the Transportation Research Board Annual Meeting, Washington D.C., USA.

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