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Should I Stop or Should I Cross? Interactions between vulnerable road users and automated vehicles

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Delft University of Technology, 2021

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Spatial and Transport Impacts of Automated Driving

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Should I stop or should I cross? Interactions between vulnerable road users and automated vehicles

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by

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"Suos cultores scientia coronat"
CGU G's

Preface

Five years ago, my PhD journey started. During my Master's degree I learned about traffic safety and how psychology was being used to improve it. I learned many ways behavior was measured and influenced to ensure the safety of the people who were travelling from A to B. I really enjoyed my studies but I was ready to get into the world and use my knowledge for the better. At SWOV, I started hearing and reading about these new up and coming vehicles that could change traffic as we know it. These so called Automated Vehicles (AVs) would make human drivers redundant and therefore make traffic much and much safer. Well, in theory that is. I wondered: Of what use is my knowledge of psychology if human drivers are removed from traffic? I was not convinced that psychology was not needed anymore. That is when I met Marjan.

Marjan informed me of a PhD position opening on the topic of AVs and traffic safety. More specifically, she was interested in measuring the effects AVs would have on traffic safety within an urban environment. I was instantly interested. In April 2016, I began my PhD research. That's when the fun started. I had to figure out how to measure the effects of a vehicle that was not on the roads yet and that had many, many possible features. The first year, I drowned in the many possibilities. I had a hard time identifying what I should focus on. Fortunately, I was supervised by a great team and therefore my PhD journey came to a successful end. This book is the evidence.

So, I would like to thank my supervisors, Marjan, Haneen and Bart, for all their support, encouragement, critical thinking and their trust. Marjan, thank you for believing in me and helping me grow as a psychologist, researcher and as a person. Haneen, thank you for being there when I needed help and helping me get back on track when I got lost in the literature. Bart, thank you for always setting up new challenges and for keeping my well-being in mind. It was not always easy to have three supervisors who all had a different perspective on the matter but I had a lot of fun and learned a great deal from sharing my journey with the three of you.

Of course, my supervisors were not the only people with whom I interacted at TU Delft. I had more colleagues around me these five years that I would like to thank. First of all, my roommates. Thank you Reanne, Yihong, Bahman, Jeroen, Goof, Louise, Ties, Maryna, Aries, Koen, Rafael, and Meiqi for the (random) discussions, language lessons, coffee breaks, jokes, snacks, and many many talks we have had. Thanks to my T&P colleagues: María, Ding, Panchamy, Solmaz, Paul, Paul, Jishnu, Konstanze, Boudewijn, Alexandra, Giulia, Marie-Jette, Danique, Lara, Niharika, Silvia, Freddy, Dorine, Rob, Maaike, Malvika, Solmaz, Peyman, Yan, Martijn, Bernat, Boudewijn, Arjan, Yongqi, Nejc, Leonie, Sina, Sanmay, Johan, Xavi, Siri, Roy, Vincent and Nagarjun. Thanks to Peter, Edwin, Priscilla Lin, Winnie, Victor, Egidio, Michiel, Lori, Hans, Niels, Meng, Maria, Gonçalo, Oded, Azita, Serge, Joelle and Simeon for the talks about everything on the corridor in between meetings. It was a treat having colleagues with different backgrounds. I enjoyed our exchange of culture, experiences, traditions, language, ideas, and of course food.

Special thanks goes to Tin, Alessandro, Tim, Nikola, Florian, Alphonse, Martijn, Vincent, Nikola, Bahman, and Boudewijn for the many sporty adventures we enjoyed. You made sure I had to finish my work on time because otherwise I could not join our football matches or bouldering appointments. This was also true for all the many dinners, (board)games, and borrels I had with Bahman, Florian, Paul, Boudewijn, Solmaz, Jishnu, Alexandra, Alessandro, Vincent, Ding, Yihong, Paul, Giulia, María, Nagarjun, Bahman, Reanne and Martijn. This last year I learned I was going to become a father and Tim, Alessandro, Tin, and Paul really helped me by answering my many questions and giving fatherly advice.

I would like to thank TRAIL Conchita, Ester, Vincent, Bert and the PhD council for their efforts to guide me and my fellow colleagues through our PhD. Also, I would like to thank my fellow PhD colleagues from the STAD-project: Baiba, Francis, Anirudh, Bahman, Reanne, and Jeroen. I am going to miss our dinners, STAD meetings and endless talks about our future and that of automated vehicles. My thanks goes out to our STAD partners for joining the meetings and giving your thoughts and feedback on our research. I was lucky to be able to join ITS Leeds and I would like to thank my supervisors Natasha, Yee Mun and Jim for your guidance and wisdom. I enjoyed doing research together and I learned so much from you.

Since the first of July, I started working at Rijkswaterstaat while finishing my PhD dissertation. I would like to thank my colleagues, especially my colleagues from cluster Verkeersveiligheid for welcoming with open arms and for your support.

Finally, I would like to thank my family and friends for their endless warmth, support and for all the fun we have had and will have. I would like to thank Marnix, Kiki and Bruno in particular for being there for me always. We have shared so many things, good and bad. I am looking forward to see where life takes us. Ik wil Linda, Lotte, Erica, Jovanna en Alex bedanken dat jullie mij met open armen hebben ontvangen in jullie familie.

Quiero agradecer a mi familia que aunque viven lejos siempre estuvieron cerca. Quiero agradecer en especial a mis abuelos que siempre han creido en mi y me han apoyado toda mi vida. Gori y pa, mil gracias por su amor, cariño y apoyo. No sé como agradecerles todo lo que han hecho por mi y por mis hermanos. Bernardo, Santiago, Andrea, Daniela en Rebeca bedankt voor jullie steun. Ik heb zoveel genoten om met jullie op te groeien en het is zo bizar om te zien hoe groot jullie al zijn en hoe jullie nu elk jullie eigen leven leiden. Ik had mij geen betere broertjes en zusjes kunnen wensen.

Als allerlaatste wil ik Merlijn en Lucía bedanken, te beginnen met de kleinste. Lucía, toen ik mijn PhD begon had ik geen idee dat jij er zou zijn voor het einde. Ik geniet enorm van hoe je groeit en ontwikkelt en ik kan mij nu al geen leven zonder jou voorstellen. Merlijn, kleine, ik kan niet in woorden omschrijven hoeveel jij voor mij betekent. Wij hebben lief en leed met elkaar gedeeld, jij was er altijd door dik en dun. Het is mij gelukt om mijn PhD te behalen en ik had het niet gekund zonder jou, zonder jouw engelengeduld en zonder jouw onvermoeidbare steun. Ik hou enorm veel van jou en van onze kleine Lucía. Bedankt.

Pablo

Leiden, May 2021

Summary

Automated vehicles (AVs) are a collection of automated driving systems that are designed to take over some or all of the driving tasks from drivers. The Society of Automotive Engineers distinguishes 6 levels of vehicle automation, ranging from no automation (level 0) to fully AVs (level 5; SAE International, 2018). In low levels of automation, the vehicle takes over some tasks from the driver such as steering and/or braking, but still relies on the driver to take over in emergency situations. The driver must supervise the vehicle, and thus pay attention at all times. When a vehicle is fully automated the 'driver' is not involved in the driving task any longer, even a driver's presence is no longer required. However, other road users, such as human driven vehicles, will still have to interact with AVs, and pedestrians and cyclists will still be part of the traffic system. In these situations, the pedestrians and cyclists might not be able to communicate with a driver and they might have to resort to a different manner of road negotiation.

Nowadays, according to the World Health Organisation (2018b) worldwide 26% of road user deaths are vulnerable road users (VRUs; e.g. pedestrians and cyclists). In the Netherlands, where most of the research in this thesis was conducted, 42% of the road deaths are pedestrians and cyclists (SWOV, 2019). The main cause of VRUs' fatalities are collisions with a motorized vehicle at an intersection in urban areas. AVs are expected to be able to react faster and more accurately due to their sensors and therefore reduce the chance of a collision. However, AVs' drivers may be less attentive or occupied with other activities when the vehicle is driving in automated mode, taking away the possibility for VRUs to communicate with a human. The negotiation of the road will still take place, but it is unclear how this will happen and what the effects will be on the safety of VRUs. So, it is important that AVs and VRUs are able to safely interact to decrease the fatalities and injuries among pedestrians and cyclists. The challenges for VRUs will be to understand the intentions of AVs, and to interact with them safely. However, only a few studies have been performed on this topic to develop insights into how VRUs behave when interacting with AVs and to unravel the underlying mechanisms that led to their behavior.

Urban areas and, more specifically intersections, are the most dangerous locations for the interactions between VRUs and motorized vehicles. In addition, crossing the road is the most risky maneuver because it could expose VRUs to motorized vehicles (AVs or conventional vehicles (CVs)) directly. Therefore, this dissertation focussed on crossing behavior in urban areas. The manner in which the VRUs cross the road when interacting with AVs compared to when interacting with CVs can reveal how VRUs perceive them and adapt their behavior accordingly. Currently, AVs that are operating on public roads are scarce. In addition, performing a road crossing experiment in the field would have caused practical and ethical

difficulties. Therefore, the empirical studies in this dissertation were performed using virtual reality.

The main aim of this dissertation is to understand the behavior of pedestrians and cyclists when interacting with an AV. The role of several characteristics of AVs such as their physical appearance, whether or not there is a driver present in the vehicle, and the presence of external communication interfaces (i.e. screens mounted on AVs to communicate with other road users) were investigated. AVs' physical appearance may differ from contemporary vehicles. Automation could make it possible for vehicles to operate without (attentive) drivers, but whether the lack of the possibility to interact with a driver affects VRUs' behavior is unclear. In addition, factors pertaining to the behavior of the vehicle (i.e. motion cues) and psychological factors, such as trust and perceived behavioral control of pedestrians and cyclists, that could be affected by the presence of AVs were also investigated. Therefore, the following main and sub research questions have been defined:

> To what extent do AVs affect the crossing behavior of pedestrians and cyclists?

1. What are the underlying factors that determine vulnerable road users' crossing behavior when interacting with an AV and how could AVs affect these factors and VRUs' crossing behavior?

2. How do the physical appearance and eHMI of an AV affect pedestrians' crossing intentions in comparison to vehicles' motion cues and psychological factors?

3. How does the physical appearance of an AV affect cyclists' crossing intentions in comparison to vehicles' motion cues and psychological factors?

4. How does the presence and attentiveness of drivers in an AV affect pedestrians' crossing behavior in comparison to vehicles' motion cues and psychological factors?

5. How does Virtual Reality perform as a research method in terms of realism, validity and ease of use?

These research questions were investigated in empirical studies and are presented in *Chapters 3*, *4*, and *5* of this dissertation.

Theoretical framework of the interaction between AVs and VRUs (RQ1)

In *Chapter 2*, I proposed a theoretical framework (figure I) which describes the interactions between AVs and road user behavior under different road design conditions. This is a prerequisite to understand how to design safe urban environments where VRUs and AVs can interact safely. A synthesis of the existing literature about the interactions between AVs and VRUs is presented. In addition the main key factors that could influence VRUs' behavior, namely road design and the AV, are included. The Theory of Planned Behavior was chosen as a basis for the proposed theoretical framework and it was extended by adding the constructs of trust and expectations. Arguably, AVs will change individuals perceived behavioral control (i.e. the control one perceives to have to successfully carry out the behavior) by affecting their expectations and their trust in AVs and therefore affect the VRUs' behavioral intentions and behavior. In addition, a feedback loop resulting from the interactions has been added to the framework. The proposed theoretical framework is designed to provide a better understanding of the mechanisms that affect road users' behavior when interacting with AVs, and in a later stage predict road users' behavior in such interactions.

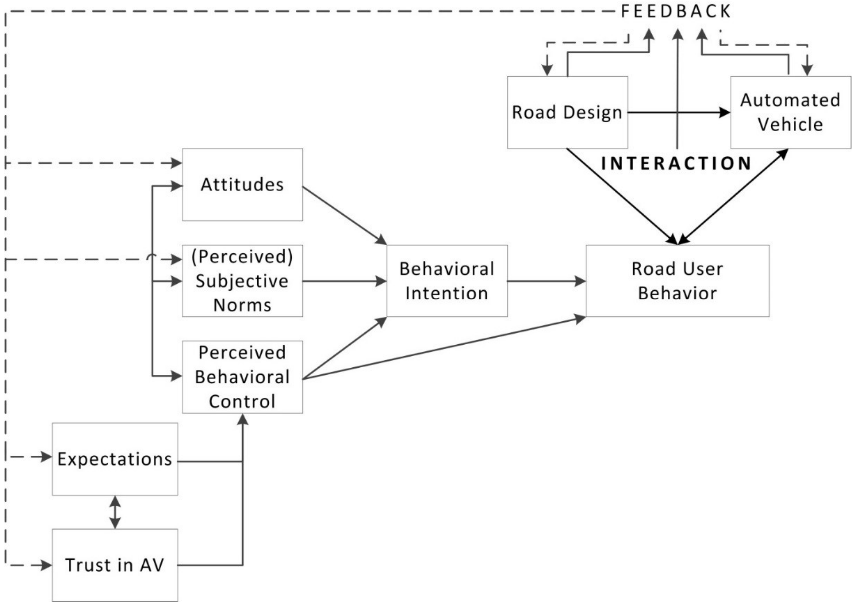


Figure I. Our theoretical framework as proposed in Chapter 2.

Automation factors, psychological factors and vehicles' motion cues effects on pedestrians' crossing intentions (RQ2)

In *Chapter 3,* I investigated how the physical appearance of AV and a mounted external human-machine interface (eHMI) affected pedestrians' crossing intention. The second aim of the chapter was to assess the perceived realism of Virtual reality based on 360° videos for pedestrian crossing intentions for research purposes. The speed, time gap, and an eHMIs were included in the study as independent factors. Pedestrians' crossing intentions were recorded, as well as their trust in automation and perceived behavioral control. I found the presence of a zebra crossing and larger gap size between the pedestrian and the vehicle increase the pedestrian's intention to cross. In contrast to our expectations, participants intended to cross less often when the speed of the vehicle was lower. Despite that the vehicle type affected the perceived risk, no significant difference was found in the crossing intention. However, pedestrians who did recognize the vehicle as an AV had lower intentions to cross, overall. A strong positive relationship was found between crossing intentions and perceived behavioral control. A difference in trust was found between pedestrians who recognized the vehicle as automated, but this did not lead to a difference in crossing intentions.

Automation factors, psychological factors and vehicles' motion cues effects on cyclists' crossing intentions (RQ3)

In *Chapter 4*, the main factors were determined influencing cyclists' crossing intentions when interacting with an automated vehicle as compared to a conventional vehicle (CV) using a 360° video-based Virtual Reality (VR) method. The considered factors in this study included vehicle type, gap size between cyclist and vehicle, vehicle speed, right of way and cyclist's self-reported behavior and trust in AVs. Only after the first session, the participants were told that one of the vehicles was an automated vehicle. This study was developed to determine the main factors influencing cyclists' intentions whether to slow down, continue cycling with the same speed or cycle faster.

The gap size and the right of way were found to be the primary factors affecting the crossing intentions of the individuals. The vehicle type and vehicle speed did not have a significant effect on the crossing intentions. Cyclists' statements whether they trusted AVs more or less as compared to CVs were found to be a stronger predictor of the crossing intentions compared to their Trust in AVs by itself. Furthermore, cyclists that reported to be low risk seeking cyclists, had higher intention to adapt their speed more than those that reported to be a high risk seeking cyclist. Overall, a positive relation was found between cycling speed adaptation and perceived behavioural control, and a negative relation between cycling speed adaptation and perceived risk, when interacting with an AV compared to a CV.

Driver's conditions and vehicles' motion cues effects on pedestrians' crossing behavior (RQ4)

In *Chapter 5*, it was determined whether drivers' presence and apparent attentiveness in a vehicle influence pedestrians' crossing behavior, perceived behavioral control, and perceived risk, in a controlled environment, using a Head-mounted Display in an immersive Virtual Reality study.

The VR environment consisted of a single lane one-way road with car traffic approaching from the right-hand side which travelled at 30 kmph. The effect of three driver conditions on pedestrians' crossing behavior were studied: Attentive driver, distracted driver, and no driver present. Two vehicles were employed with a fixed time gap (3.5 s and 5.5s) between them to study the effects of time gaps on pedestrians' crossing behavior. The manipulated vehicle yielded to the pedestrians in half of the trials, stopping completely before reaching the pedestrian's position. The crossing decision, time to initiate the crossing, crossing duration, and safety margin were measured.

The main findings show that the vehicle's motion cues (i.e. the gap between the vehicles, and the yielding behavior of the vehicle) were the most important factors affecting pedestrians' crossing behavior. Interestingly, perceiving vehicles as automated led to riskier crossing behavior such as taking longer to cross the road. Contrary to expectations, the no driver condition did not have a significant effect on pedestrians' crossing behavior. Only the distracted driver condition had a small but significant effect. Questionnaire results show that pedestrians felt they had more control, and felt safer, when the driver was present and attentive. The simulator realism scale showed that the virtual reality experiment was acceptable to the participants.

Performance of Virtual Reality (VR) as a research method (RQ5)

In *Chapter 3* the 360° video-based VR research methodology was assessed using the presence questionnaire, the simulation sickness survey, and by comparing the results with previous literature. The method scored highly on the presence questionnaire and only a small percentage of the participants stopped prematurely. Thus, the research methodology is useful for crossing behavior experiments. This was in congruence with our findings in *Chapter 4*. The 360° video-based VR methodology was perceived as realistic. In addition, almost every participant finished the experiment without any significant simulation sickness symptoms. This is comparable with the results of previous studies investigating pedestrians' crossing intentions confirming the suitability of 360° video-based VR methodology as a research methodology to study cyclists' crossing intentions. The immersive VR research methodology was also used and evaluated in *Chapter 5.* In terms of realism, the scores on the presence scale are good overall, except on the interface quality. The scores on the misery scale were good and showed that the participants

experienced vague symptoms of simulation sickness at most. Mostly, no symptoms were experienced. Overall, it can be concluded that this type of virtual reality proved to be useful for this kind of studies.

Conclusion
This dissertation has contributed to the understanding of crossing behavior of VRUs when interacting with AVs and of the underlying mechanisms of crossing behavior. The factors pertaining to each of the three components (i.e. AVs, VRUs, & infrastructure), that together form the interaction, are relevant. The presented findings show that AVs do not have an effect on VRUs' road crossing behavior in the short term. However, this depends on whether AVs will behave in-line with the VRUs' expectations. Psychologically, AVs affected the VRUs but it did not result in behavioural adaptation. The psychological constructs that were shown to be affected by the AV, were perceived behavioral control, trust in AVs, perceived risk, and familiarity with AVs. The results of this dissertation show that the vehicle factors, in particular the distance between the AV and the VRU (i.e. the gap size), was the most important factor affecting the VRUs' crossing intentions in the short term. The vehicles' motion cues were found to have a stronger effect on crossing behavior compared to automation factors. VRUs are able to make crossing decisions based on the motion cues of the vehicle possibly due to their prelearned road crossing strategies.

This dissertation used 360° videos and immersive virtual reality technologies, and questionnaires to study the road crossing intentions and behavior of pedestrians and cyclists when interacting with AVs. The types of VR employed during the presented experiments performed adequately and shows that this type of methodology is helpful to find relevant factors and trends that could also be found in the real world. However, more research on the transferability of results is needed.

This dissertation contributed to the growing literature on the interactions between AVs and VRUs but still more research is needed. The recommendations for future work include investigating the effects of age, educational level, and cultural differences and focus on a wider variety of behaviors and how these behaviours are affected by AVs. More research is needed to identify how AVs will behave and how this could affect the behavior of VRUs. Future work should try to focus more on answering the question when eHMIs should be used and when it should not.

The research was performed in a controlled setting and the scenarios included were limited. This results in a limited transferability for practice. However, some implications for practice can be mentioned. Municipalities should be encouraged to implement pilots which contain AVs and also focus on studying the interactions between VRUs and AVs. External human machine interfaces should be used with care. Vehicle manufacturers should consider the intended use of the vehicle before making large scale use of specific eHMIs. It is recommended to also develop specific vehicles' motion cues which make the intentions of the vehicle clear. Finally, information and education towards VRUs should not only focus on the capabilities of AVs but also on the limitations.

Samenvatting

Geautomatiseerde voertuigen (AVs) zijn een verzameling van geautomatiseerde rijsystemen die zijn ontworpen om sommige of alle rijtaken van bestuurders over te nemen. De Society of Automative Engineers onderscheidt 6 niveaus van voertuigautomatisering, variërend van geen automatisering (niveau 0) tot volledig AVs (niveau 5; SAE International, 2018). Bij lage automatiseringsniveaus neemt het voertuig enkele taken van de bestuurder over, zoals sturen en/of remmen, maar vertrouwt het nog steeds op de bestuurder om deze taken in noodsituaties weer over te nemen. De bestuurder moet toezicht houden op het voertuig, en dus te allen tijde opletten. Wanneer een voertuig volledig is geautomatiseerd, is de "bestuurder" niet langer betrokken bij de rijtaak en is zelfs de aanwezigheid van een bestuurder niet langer vereist. Andere weggebruikers, zoals door mensen bestuurde voertuigen, zullen echter nog steeds interactie moeten hebben met AVs, en voetgangers en fietsers zullen nog steeds deel uitmaken van het verkeerssysteem. In deze situaties kunnen de voetgangers en fietsers mogelijk niet communiceren met een bestuurder en zullen ze hun toevlucht moeten nemen tot een andere manier van onderhandelen op de weg.

Op dit moment zijn volgens de Wereldgezondheidsorganisatie (2018b) wereldwijd 26% van de verkeersdoden kwetsbare verkeersdeelnemers (VRUs; oftewel voetgangers en fietsers). In Nederland, waar het grootste deel van het onderzoek in deze scriptie is uitgevoerd, bestaat 42% van de verkeersdoden uit voetgangers en fietsers (SWOV, 2019). De belangrijkste oorzaak van de dodelijke slachtoffers onder VRUs zijn aanrijdingen met een gemotoriseerd voertuig op een kruispunt in stedelijke gebieden. De verwachting is dat AVs door hun sensoren sneller en nauwkeuriger kunnen reageren en daarmee de kans op een aanrijding verkleinen. De bestuurders van AVs kunnen echter minder oplettend zijn of met andere activiteiten bezig zijn wanneer het voertuig in geautomatiseerde modus rijdt, waardoor de mogelijkheid voor AVs om met een mens te communiceren wordt weggenomen. Er zal nog steeds onderhandeling over de weg plaatsvinden, maar het is onduidelijk hoe dit zal gebeuren en wat de gevolgen zullen zijn voor de veiligheid van VRUs. Het is dus belangrijk dat AVs in staat zijn veilig deel te nemen in het verkeer met VRUs om het aantal doden en gewonden onder voetgangers en fietsers te verminderen. De uitdagingen voor bestuurders van voertuigen zullen erin bestaan de bedoelingen van voertuigen te begrijpen en veilig met hen om te gaan. In 2016 waren de interacties tussen AVs en VRUs een onderzoekshiaat. Tot dan toe waren er slechts enkele studies uitgevoerd over het onderwerp. Het doel was om inzichten te creëren in hoe VRUs zich gedroegen bij interacties met AVs en om de onderliggende mechanismen te ontrafelen die tot dat gedrag leidden.

Stedelijke gebieden, en meer specifiek kruispunten, zijn de gevaarlijkste locaties voor interacties tussen VRUs en gemotoriseerde voertuigen. Bovendien is het oversteken van de weg de meest riskante manoeuvre omdat het VRUs direct kan blootstellen aan gemotoriseerde voertuigen (AVs of conventionele voertuigen (CVs)). Daarom richtte deze dissertatie zich op

oversteekgedrag in stedelijke gebieden. De manier waarop VRUs de weg oversteken wanneer ze in aanraking komen met AVs in vergelijking met CVs kan onthullen hoe VRUs hen waarnemen en hoe ze hun gedrag aanpassen. Momenteel zijn er maar weinig AVs die op de openbare weg rijden. Bovendien zou het uitvoeren van een oversteekexperiment op de openbare weg praktische en ethische problemen hebben veroorzaakt. Daarom werden de empirische studies die voor dit proefschrift werden uitgevoerd, uitgevoerd met behulp van virtual reality.
Het hoofddoel van dit proefschrift is het gedrag van voetgangers en fietsers te begrijpen wanneer ze deel nemen in het verkeer met een AV. De rol van verschillende kenmerken van AVs, zoals hun fysieke verschijning, het al dan niet aanwezig zijn van een bestuurder in het voertuig, en de aanwezigheid van externe communicatie-interfaces (eHMI; d.w.z. schermen gemonteerd op AVs om te communiceren met andere weggebruikers) werden onderzocht in dit proefschrift. Het fysieke verschijning van AVs kan verschillen van hedendaagse voertuigen. Automatisering zou het voor voertuigen mogelijk kunnen maken om zonder (oplettende) bestuurder te handelen, maar of het ontbreken van de mogelijkheid tot interactie met een bestuurder het gedrag van AVs beïnvloedt is onduidelijk. Daarnaast werden ook factoren onderzocht met betrekking tot het gedrag van het voertuig (bijv. bewegingscues) en psychologische factoren, zoals het vertrouwen en de mate waarin controle over de situatie werd ervaren bij voetgangers en fietsers, die beïnvloed zouden kunnen worden door de aanwezigheid van AVs. Deze dissertatie richt zich op oversteekgedrag in stedelijke gebieden. De manier waarop VRUs de weg oversteken bij interactie met AVs in vergelijking met de interactie met conventionele voertuigen (CVs) kan duidelijk maken hoe VRUs deze voertuigen waarnemen en of en hoe ze hun gedrag aanpassen. Daarom werden de volgende hoofd- en deelonderzoeksvragen gedefinieerd:

> In welke mate beïnvloeden AVs het oversteekgedrag van voetgangers en fietsers?

1. Wat zijn de onderliggende factoren die het oversteekgedrag van kwetsbare weggebruikers bepalen bij interactie met een AV en hoe kunnen AVs deze factoren en het oversteekgedrag van kwetsbare weggebruikers beïnvloeden?

2. Hoe beïnvloeden het fysieke verschijning en de eHMI van een AV de oversteekintentie van voetgangers in vergelijking met de bewegingscues van voertuigen en psychologische factoren?

3. Hoe beïnvloedt de fysieke verschijning van een AV de oversteekintentie van fietsers in vergelijking met de bewegingscues van het voertuig en psychologische factoren?

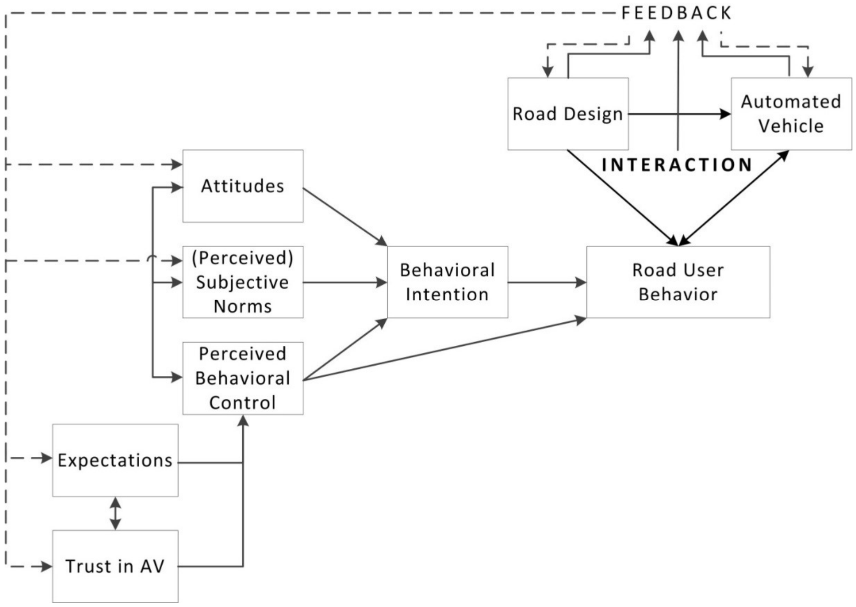
4. Hoe beïnvloedt de aanwezigheid en oplettendheid van bestuurders in een AV het oversteekgedrag van voetgangers in vergelijking met de bewegingscues van voertuigen en psychologische factoren?

5. Hoe presteert Virtual Reality als onderzoeksmethode in termen van realisme, validiteit en gebruiksgemak?

Deze onderzoeksvragen werden onderzocht in empirische studies en worden gepresenteerd in *de hoofdstukken 3*, *4*, en *5* van dit proefschrift.

Theoretisch kader van de interactie tussen AVs en bestuurders van voertuigen (vraag 1)

In *hoofdstuk 2,* heb ik een theoretisch kader voorgesteld (figuur II) dat de interacties beschrijft tussen AVs en het gedrag van weggebruikers onder verschillende wegontwerpomstandigheden. Dit is een eerste vereiste om te begrijpen hoe veilige stedelijke omgevingen kunnen worden ontworpen waar VRUs en AVs veilig met elkaar deel kunnen nemen in het verkeer. Een overzicht van de bestaande literatuur over de interacties tussen AVs en VRUs wordt gepresenteerd. Daarnaast worden de belangrijkste spelers en factoren die het gedrag van VRUs kunnen beïnvloeden behandeld, namelijk het wegontwerp en de AVs. De Theorie van gepland gedrag werd gekozen als basis voor ons voorgestelde theoretische kader en het werd uitgebreid door de constructen vertrouwen en verwachtingen toe te voegen. Het is aannemelijk dat AVs de mate waarin gedragscontrole wordt ervaren bij individuen (d.w.z. de controle die men meent te hebben om het gedrag met succes uit te voeren) zullen veranderen door hun verwachtingen en vertrouwen in AVs te beïnvloeden. Daarmee beinvloeden AVs ook de gedragsintenties en het gedrag van de VRUs . Bovendien voegden we een feedbacklus toe aan het kader die het gevolg van de interacties beschrijft. Het voorgestelde theoretische kader is ontworpen om beter inzicht te krijgen in de mechanismen die het gedrag van weggebruikers beïnvloeden bij interacties met AVs, en om in een later stadium het gedrag van weggebruikers bij dergelijke interacties te voorspellen.



Figuur II. Ons theoretisch kader zoals voorgesteld in hoofdstuk 2.

Effecten van automatiseringsfactoren, psychologische factoren en bewegingscues van voertuigen op de oversteekintentie van voetgangers (RQ2)

In *hoofdstuk 3,* werd onderzocht hoe de fysieke verschijning van AVs en een gemonteerde externe mens-machine interface (eHMI) de oversteekintentie van voetgangers beïnvloedde. Het tweede doel van het hoofdstuk was het beoordelen van het waargenomen realisme van Virtual Reality op basis van 360° video's voor het oversteekgedrag van voetgangers voor onderzoeksdoeleinden. De snelheid, tijdsverschil en een eHMI werden als onafhankelijke factoren meegenomen in de studie. De oversteekintenties van voetgangers werden geregistreerd, evenals hun vertrouwen in automatisering en de mate waarin controle over het gedrag werd ervaren. We vonden dat de aanwezigheid van een zebrapad en een grotere afstand tussen de voetganger en het voertuig de intentie van de voetganger om over te steken verhoogden. In tegenstelling tot onze verwachtingen wilden de deelnemers minder vaak oversteken wanneer de snelheid van het voertuig lager was. Ondanks dat het type voertuig de inschatting van het risico beïnvloedde, werd er geen significant verschil gevonden in de oversteekintentie. Echter, als voetgangers het voertuig herkenden als een AV dan zij hadden een lagere intentie om over te steken. Er werd een sterk positief verband gevonden tussen oversteekintentie en waargenomen gedragscontrole. Er werd een verschil in vertrouwen gevonden tussen voetgangers die het voertuig als geautomatiseerd herkenden, maar dit leidde niet tot een verschil in oversteekintentie.

Effecten van automatiseringsfactoren, psychologische factoren en bewegingscues van voertuigen op de oversteekintentie van fietsers (RQ3)

In *hoofdstuk 4,* werden, met behulp van een 360° video-gebaseerde virtual reality (VR) methode, de belangrijkste factoren bepaald die van invloed zijn op de oversteekintentie van fietsers wanneer ze in interactie zijn met een automatisch voertuig in vergelijking met een conventioneel voertuig (CV). De factoren die in deze studie in overweging zijn genomen waren onder andere: het type voertuig, de grootte van de afstand tussen fietser en voertuig, de snelheid van het voertuig, voorrang en het zelfgerapporteerde gedrag van de fietser en het vertrouwen in automatische voertuigen. Pas na de eerste sessie kregen de deelnemers te horen dat een van de voertuigen een automatisch voertuig was. Deze studie werd ontwikkeld om de belangrijkste factoren te bepalen die van invloed zijn op de intentie van fietsers om langzamer te fietsen, met dezelfde snelheid door te fietsen of sneller te fietsen.

De hoeveelheid ruimte en het recht van overpad bleken de belangrijkste factoren te zijn die de oversteekintentie van de fietsers beïnvloedden. Het voertuigtype en de voertuigsnelheid hadden geen significant effect op de oversteekintenties. De verklaringen van fietsers of ze AVs meer of minder vertrouwden ten opzichte van CVs bleken een sterkere voorspeller te zijn van de oversteekintenties dan hun vertrouwen in AVs op zich. Bovendien hadden fietsers die aangaven weinig risico te willen lopen, een hogere intentie om hun snelheid aan te passen dan fietsers die aangaven bereid te zijn veel risico te lopen. In het algemeen werd een positief verband gevonden tussen de aanpassing van de fietssnelheid en waargenomen gedragscontrole, en een negatief verband tussen de aanpassing van de fietssnelheid en het ingeschatte risico, wanneer interactie met een AV plaatsvindt in vergelijking met een CV.

Effecten van de omstandigheden van de bestuurder en van bewegingscues van voertuigen op het oversteekgedrag van voetgangers (RQ4)

In *Hoofdstuk 5,* werd bepaald of de aanwezigheid van bestuurders in een voertuig en of deze bestuurders oplettend overkomen van invloed zijn op het oversteekgedrag, de mate waarin controle over het gedrag werd ervaren en de inschatting van hetrisico van voetgangers, in een gecontroleerde omgeving, met behulp van een Head-mounted Display in een immersieve Virtual Reality studie.

De VR-omgeving bestond uit een eenrichtingsweg met één rijstrook en rechts naderend autoverkeer dat 30 km/uur reed. Het effect van drie bestuurdersomstandigheden op het oversteekgedrag van voetgangers werd bestudeerd: Oplettende bestuurder, afgeleide bestuurder, en geen bestuurder aanwezig. Twee voertuigen werden ingezet met een vast tijdsverschil (3,5 s en 5,5 s) tussen beide om de effecten van tijdsverschillen op het oversteekgedrag van voetgangers te bestuderen. Het gesimuleerde voertuig gaf voorrang aan de voetgangers in de helft van de proeven, waarbij het volledig stopte voordat het de positie van de voetganger bereikte. De beslissing om over te steken, de tijd om over te steken, de duur van het oversteken en de veiligheidsmarge werden gemeten.

De belangrijkste bevindingen tonen aan dat de bewegingsinformatie van het voertuig (d.w.z. de afstand tussen de voertuigen, en het voorrangsgedrag van het voertuig) de belangrijkste factoren waren die het oversteekgedrag van de voetgangers beïnvloedden. Interessant is dat de perceptie dat voertuigen geautomatiseerd zijn, leidt tot risicovoller oversteekgedrag, zoals langer de tijd nemen om de weg over te steken. Tegen de verwachting in had de situatie zonder bestuurder geen significant effect op het oversteekgedrag van voetgangers. Alleen de situatie met de afgeleid rijdende bestuurder had een klein maar significant effect. Uit de resultaten van de vragenlijst blijkt dat voetgangers het gevoel hadden dat ze meer controle hadden en zich veiliger voelden wanneer de bestuurder aanwezig en oplettend was. De schaal voor simulatorrealisme toonde aan dat het virtual reality-experiment aanvaardbaar was voor de deelnemers.

Prestaties van Virtual Reality (VR) als onderzoeksmethode (RQ5)

In *hoofdstuk 3,* werd de 360° video-gebaseerde VR onderzoeksmethode beoordeeld aan de hand van de aanwezigheidsvragenlijst, de simulatieziekte-enquête, en door de resultaten te vergelijken met eerdere literatuur. De methode scoorde hoog op de aanwezigheidsvragenlijst en slechts een klein percentage van de deelnemers stopte voortijdig. De onderzoeksmethode is dus bruikbaar voor gedragsexperimenten over het oversteken van een weg. Dit was in overeenstemming met onze bevindingen in *hoofdstuk 4*. De 360° video-gebaseerde VR methodologie werd als realistisch ervaren. Bovendien beëindigde bijna elke deelnemer het experiment zonder significante simulatieziektesymptomen. Dit is vergelijkbaar met de resultaten van een eerder onderzoek naar de oversteekintentie van voetgangers, wat bevestigt dat de 360° video-gebaseerde VR methodologie geschikt is als onderzoeksmethodologie om de oversteekintentie van fietsers te bestuderen. De immersieve VR onderzoeksmethodologie werd ook gebruikt en geëvalueerd in *hoofdstuk 5.* In termen van realisme zijn de scores op de Presence-scale over het algemeen goed, behalve op de interfacekwaliteit. De scores op de ellende-schaal waren goed en lieten zien dat de deelnemers hooguit vage symptomen van simulatieziekte ervoeren. Meestal werden geen symptomen ervaren. Over het geheel genomen kan worden geconcludeerd dat dit type virtual reality nuttig is gebleken voor dit soort studies.

Conclusie

Deze dissertatie heeft bijgedragen aan het begrijpen van het oversteekgedrag van gemotoriseerde voertuigen in interactie met voertuigen en het begrijpen van de onderliggende mechanismen van oversteekgedrag. De factoren die betrekking hebben op elk van de drie componenten die samen de interactie vormen (AVs, VRUs, & infrastructuur) zijn relevant. De gepresenteerde bevindingen tonen aan dat AVs op korte termijn geen effect hebben op het oversteekgedrag van VRUs. Dit hangt echter af van de vraag of AVs zich in lijn met de verwachtingen van de VRUs zullen gedragen. Er was een psychologisch effect van AVs op de voertuiggebruikers, maar dat resulteerde niet in gedragsaanpassing. De psychologische constructen waarvan werd aangetoond dat ze werden beïnvloed door het AV, waren waargenomen gedragscontrole, vertrouwen in AVs, waargenomen risico, en vertrouwdheid met AVs. De resultaten van deze dissertatie tonen aan dat de voertuigfactoren, in het bijzonder de afstand tussen het AV en de bestuurder de belangrijkste factor was die de oversteekintenties van de bestuurders op korte termijn beïnvloedde. De bewegingscues van de voertuigen bleken een sterker effect te hebben op het oversteekgedrag dan de automatiseringsfactoren. VRUs zijn in staat om oversteekbeslissingen te nemen op basis van de bewegingscues van het voertuig, mogelijk als gevolg van hun vooraf aangeleerde strategieën voor het oversteken van wegen.

Deze dissertatie gebruikte 360° video's en immersieve virtual reality technologieën, en vragenlijsten om de oversteekintenties en het gedrag van voetgangers en fietsers te bestuderen bij interactie met AVs. De VR-types die tijdens de gepresenteerde experimenten werden gebruikt, presteerden adequaat en tonen aan dat dit type methodologie nuttig is om relevante factoren en trends te vinden die ook in de echte wereld zouden kunnen worden gevonden. Meer onderzoek naar de overdraagbaarheid van de resultaten is echter nodig.

Dit proefschrift heeft bijgedragen tot de groeiende literatuur over de interacties tussen AVs en VRUs, maar er is nog meer onderzoek nodig. De aanbevelingen voor toekomstig werk op basis van dit proefschrift zijn als volgt. Toekomstig onderzoek zou de effecten van leeftijd, opleidingsniveau en culturele verschillen kunnen onderzoeken en zich kunnen richten op een grotere verscheidenheid aan gedragingen en hoe deze worden beïnvloed door AVs. Er is meer onderzoek nodig om te bepalen hoe AVs zich zullen gedragen en hoe dit het gedrag van VRUs zou kunnen beïnvloeden. Toekomstig werk moet zich meer richten op het beantwoorden van de vraag wanneer eHMI's moeten worden gebruikt en wanneer niet.

Het onderzoek werd uitgevoerd in een gecontroleerde setting en de opgenomen scenario's waren beperkt. Dit resulteert in een beperkte overdraagbaarheid van mijn resultaten naar de praktijk. Toch kunnen enkele implicaties voor de praktijk worden genoemd: Gemeenten moeten worden aangemoedigd om pilots uit te voeren die AVs bevatten en ook aandacht besteden aan het bestuderen van de interacties tussen VRUs en AVs. Externe mens/machine-interfaces moeten met zorg worden gebruikt. Voertuigfabrikanten moeten rekening houden met het beoogde gebruik van het voertuig alvorens op grote schaal gebruik te maken van specifieke eHMI's. Het wordt aanbevolen om ook specifieke bewegingscues voor voertuigen te ontwikkelen die de intenties van het voertuig duidelijk maken. Ten slotte moeten informatie en voorlichting aan bestuurders van voertuigen niet alleen gericht zijn op de mogelijkheden van AVs maar ook op de beperkingen.

Resumen

Los vehículos automatizados (AVs) son un conjunto de sistemas de conducción automatizada que están diseñados para asumir algunas o todas las tareas de conducción de los conductores. La “Society of Automative Engineers” distingue 6 niveles de automatización de vehículos, que van desde la ausencia de automatización (nivel 0) hasta los vehículos totalmente automatizados (nivel 5; SAE International, 2018). En los niveles bajos de automatización, el vehículo se hace cargo de algunas tareas del conductor, como la dirección y/o el frenado, pero sigue confiando en el conductor para que se haga cargo en situaciones de emergencia. El conductor debe supervisar el vehículo y, por tanto, prestar atención en todo momento. Cuando un vehículo está totalmente automatizado, el "conductor" ya no participa en la tarea de conducir, incluso ya no es necesaria su presencia. Sin embargo, otros usuarios de la carretera, como los vehículos conducidos por humanos, seguirán teniendo que interactuar con los AVs, y los peatones y ciclistas seguirán formando parte del sistema de tráfico. En estas situaciones, los peatones y los ciclistas podrían no ser capaces de comunicarse con un conductor y tendrían que recurrir a una forma diferente de negociación vial.

Actualmente, según la Organización Mundial de la Salud (2018b) en todo el mundo el 26% de las muertes de usuarios de la vía pública son usuarios vulnerables de la vía pública (VRUs; es decir, peatones y ciclistas). En los Países Bajos, donde se ha realizado la mayor parte de la investigación de esta tesis, el 42 % de las muertes en carretera son peatones y ciclistas (SWOV, 2019). La principal causa de las muertes de los AVs son las colisiones con un vehículo motorizado en una intersección en zonas urbanas. Se espera que los AVs sean capaces de reaccionar más rápido y con mayor precisión debido a sus sensores y, por lo tanto, reducir la posibilidad de una colisión. Sin embargo, los conductores de los AVs pueden estar menos atentos u ocupados con otras actividades cuando el vehículo está conduciendo en modo automatizado, quitando la posibilidad de que los VRUs se comuniquen con un humano. La negociación de la carretera seguirá teniendo lugar, pero no está claro cómo ocurrirá y cuáles serán los efectos en la seguridad de los VRUs. Por lo tanto, es importante que los AVs sean capaces de interactuar de forma segura con los VRUs para disminuir las muertes y lesiones entre los peatones y ciclistas. Los retos para los vehículos todo terreno serán comprender las intenciones de los vehículos automáticos e interactuar con ellos de forma segura. En 2016, las interacciones entre los AVs y los VRUs eran una laguna en la investigación. Hasta entonces solo se habían realizado unos pocos estudios sobre el tema. El objetivo era comprender cómo se comportaban los VRUs al interactuar con los AVs y desentrañar los mecanismos subyacentes que conducían a dicho comportamiento.

Las zonas urbanas y, más concretamente, las intersecciones son los lugares más peligrosos para las interacciones entre los VRUs y los vehículos motorizados. Además, cruzar la carretera es la

maniobra más arriesgada porque puede exponer a los VRUs a los vehículos motorizados (AVs o vehículos convencionales (CVs)) directamente. Por lo tanto, esta disertación se centró en el comportamiento de cruce en zonas urbanas. La forma en que los VRUs cruzan la carretera cuando interactúan con AVs en comparación con cuando interactúan con CVs puede revelar cómo los VRUs los perciben y adaptan su comportamiento. Actualmente, los AVs que circulan por las vías públicas son escasos. Además, la realización de un experimento de cruce de carreteras sobre el terreno habría causado dificultades prácticas y éticas. Por lo tanto, los estudios empíricos realizados para esta disertación se llevaron a cabo utilizando la realidad virtual.

El objetivo principal de esta tesis es comprender el comportamiento de los peatones y ciclistas cuando interactúan con un AVs. En esta tesis se investigó el papel de varias características de los AVs, como su aspecto físico, la presencia o no de un conductor en el vehículo y la presencia de interfaces de comunicación externas (es decir, pantallas montadas en los AVs para comunicarse con otros usuarios de la vía pública). El aspecto físico de los AVs puede diferir del de los vehículos actuales. La automatización podría hacer posible que los vehículos funcionaran sin conductores (atentos), pero no está claro si la falta de posibilidad de interactuar con un conductor afecta al comportamiento de los AVs. Además, también se investigaron los factores relativos al comportamiento del vehículo (es decir, las señales de movimiento) y los factores psicológicos, como la confianza y el control conductual percibido, de los peatones y ciclistas que podrían verse afectados por la presencia de los AVs. Esta tesis se centra en el comportamiento de cruce en zonas urbanas. La forma en que los VRUs cruzan la carretera cuando interactúan con AVs en comparación con cuando interactúan con vehículos contemporáneos (CVs) puede revelar cómo los VRUs los perciben y si adaptan su comportamiento y cómo lo hacen. Por lo tanto, se han definido las siguientes preguntas principales y secundarias de investigación:

> ¿En qué medida afectan los vehículos automáticos al comportamiento de los peatones y ciclistas al cruzar la calle?
>
> 1. ¿Cuáles son los factores subyacentes que determinan el comportamiento de cruce de los usuarios vulnerables de la vía pública cuando interactúan con un AV y cómo podrían los AVs afectar a estos factores y al comportamiento de cruce de los VRUs?
>
> 2. ¿Cómo influyen el aspecto físico y la “external human-machine interfaces” (eHMI) de un AV en la intención de cruzar de los peatones en comparación con las señales de movimiento de los vehículos y los factores psicológicos?
>
> 3. ¿Cómo afecta la apariencia física de un AV a las intenciones de cruce de los ciclistas en comparación con las señales de movimiento de los vehículos y los factores psicológicos?
>
> 4. ¿Cómo afecta la presencia y la atención de los conductores en un AV al comportamiento de los peatones al cruzar, en comparación con las señales de movimiento de los vehículos y los factores psicológicos?
>
> 5. ¿Cómo funciona la realidad virtual como método de investigación en términos de realismo, validez y facilidad de uso?

Estas preguntas de investigación se investigaron en estudios empíricos y se presentan en *los capítulos 3*, *4* y *5* de esta disertación.

Marco teórico de la interacción entre los AVs y los VRUs (RQ1)

En *el capítulo 2*, propusimos un marco teórico (figura III) que describe las interacciones entre los vehículos automatizados y el comportamiento de los usuarios de la vía pública en diferentes condiciones de diseño vial. Este es un requisito previo para entender cómo diseñar entornos urbanos seguros en los que los VRUs y los vehículos automatizados puedan interactuar de forma segura. Se presenta una síntesis de la literatura existente sobre las interacciones entre los vehículos automatizados y los VRUs. Además, se incluyen los principales actores y factores clave que podrían influir en el comportamiento de los VRUs, es decir, el diseño de la carretera y el AV. Se eligió la Teoría del Comportamiento Planificado como base para nuestro marco teórico propuesto y se amplió añadiendo los constructos de confianza y expectativas. Podría decirse que los AVs cambiarán el control conductual percibido por los individuos (es decir, el control que uno percibe tener para llevar a cabo con éxito el comportamiento) afectando a sus expectativas y a su confianza en los AVs y, por lo tanto, afectando a las intenciones conductuales y al comportamiento de los VRUs. Además, se ha añadido al marco un ciclo de retroalimentación resultante de las interacciones. El marco teórico propuesto está diseñado para proporcionar una mejor comprensión de los mecanismos que afectan al comportamiento de los usuarios de la carretera cuando interactúan con los AVs, y en una etapa posterior predecir el comportamiento de los usuarios de la carretera en tales interacciones.

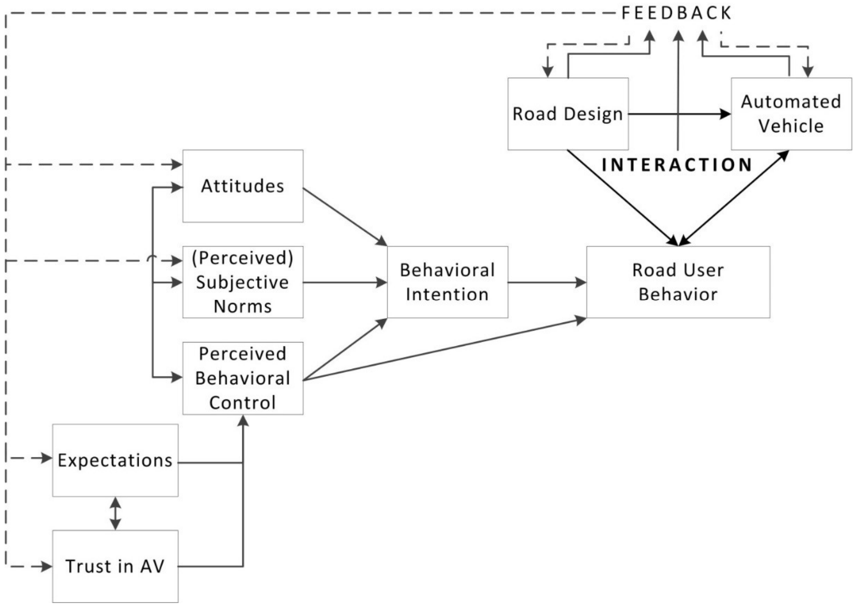


Figura III. Nuestro marco teórico propuesto en el capítulo 2.

Efectos de los factores de automatización, los factores psicológicos y las señales de movimiento de los vehículos en la intención de cruzar de los peatones (RQ2)

En *el capítulo 3 se* investigó cómo la apariencia física del AV y una interfaz hombre-máquina externa (eHMI) montada afectaban a la intención de cruzar de los peatones. El segundo objetivo del capítulo era evaluar el realismo percibido de la realidad virtual basada en vídeos de 360º para el comportamiento de cruce de los peatones con fines de investigación. Se incluyeron en el estudio la velocidad, el intervalo de tiempo y un eHMI como factores independientes. Se registraron las intenciones de cruce de los peatones, así como su confianza en la automatización y el control conductual percibido. Descubrimos que la presencia de un paso de cebra y un mayor espacio entre el peatón y el vehículo aumentan la intención de cruzar del peatón. En contraste con nuestras expectativas, los participantes tenían menos intención de cruzar cuando la velocidad del vehículo era menor. A pesar de que el tipo de vehículo afectaba al riesgo percibido, no se encontraron diferencias significativas en la intención de cruzar. Sin embargo, los peatones que reconocían el vehículo como un AV tenían una menor intención de cruzar, en general. Se encontró una fuerte relación positiva entre la intención de cruzar y el control conductual percibido. Se encontró una diferencia en la confianza entre los peatones que reconocieron el vehículo como automatizado, pero esto no condujo a una diferencia en las intenciones de cruzar.

Efectos de los factores de automatización, los factores psicológicos y las señales de movimiento de los vehículos en las intenciones de cruce de los ciclistas (RQ3)

En *el capítulo 4* determiné los principales factores que influyen en las intenciones de cruce de los ciclistas cuando interactúan con un vehículo automatizado en comparación con un vehículo convencional (CV) utilizando un método de Realidad Virtual (RV) basado en un vídeo de 360º. Los factores considerados en este estudio incluían el tipo de vehículo, el tamaño del espacio entre el ciclista y el vehículo, la velocidad del vehículo, el derecho de paso y el comportamiento autodeclarado del ciclista y su confianza en los vehículos automatizados. Sólo después de la primera sesión, se comunicó a los participantes que uno de los vehículos era un vehículo automatizado. Este estudio se desarrolló para determinar los principales factores que influyen en la intención de los ciclistas de reducir la velocidad, seguir pedaleando a la misma velocidad o hacerlo más rápido.

El tamaño del hueco y el derecho de paso resultaron ser los principales factores que afectaban a las intenciones de cruzar de los individuos. El tipo de vehículo y la velocidad del mismo no tuvieron un efecto significativo en las intenciones de cruzar. Las declaraciones de los ciclistas sobre si confiaban más o menos en los AVs en comparación con los CVs resultaron ser un predictor más fuerte de las intenciones de cruzar en comparación con su confianza en los AVs por sí misma. Además, los ciclistas que declararon ser ciclistas que buscan poco riesgo, tenían mayor intención de adaptar su velocidad que los que declararon ser ciclistas que buscan mucho riesgo. En general, se encontró una relación positiva entre la adaptación de la velocidad ciclista y el control conductual percibido, y una relación negativa entre la adaptación de la velocidad ciclista y el riesgo percibido, cuando se interactúa con un AVs en comparación con un CV.

Efectos de las condiciones del conductor y de las señales de movimiento de los vehículos en el comportamiento de los peatones al cruzar (RQ4)

En *el capítulo 5* determiné si la presencia y la atención aparente de los conductores en un vehículo influyen en el comportamiento de los peatones al cruzar, en el control conductual percibido y en el riesgo percibido, en un entorno controlado, utilizando una pantalla montada en la cabeza en un estudio de realidad virtual inmersiva.

El entorno de RV consistía en una carretera de un solo carril de sentido único con tráfico de coches que se acercaba por el lado derecho y que circulaba a 30 km/h. Se estudió el efecto de tres condiciones del conductor sobre el comportamiento de los peatones al cruzar: Conductor atento, conductor distraído y sin conductor presente. Se emplearon dos vehículos con un intervalo de tiempo fijo (3,5 s y 5,5 s) entre ellos para estudiar los efectos de los intervalos de tiempo en el comportamiento de cruce de los peatones. El vehículo manipulado cedió el paso a los peatones en la mitad de los ensayos, deteniéndose completamente antes de llegar a la posición del peatón. Se midió la decisión de cruzar, el tiempo para iniciar el cruce, la duración del cruce y el margen de seguridad.

Los principales resultados muestran que las señales de movimiento del vehículo (es decir, el espacio entre los vehículos y el comportamiento de ceder el paso del vehículo) fueron los factores más importantes que afectaron al comportamiento de los peatones al cruzar. Curiosamente, percibir los vehículos como automatizados condujo a un comportamiento de cruce más arriesgado, como tardar más en cruzar la carretera. Al contrario de lo que se esperaba, la condición de no tener conductor no tuvo un efecto significativo en el comportamiento de los peatones al cruzar. Sólo la condición de conductor distraído tuvo un efecto pequeño pero significativo. Los resultados del cuestionario muestran que los peatones sentían que tenían más control y se sentían más seguros cuando el conductor estaba presente y atento. La escala de realismo del simulador mostró que el experimento de realidad virtual era aceptable para los participantes.

Rendimiento de la Realidad Virtual (RV) como método de investigación (RQ5)

En *el capítulo 3* se evaluó la metodología de investigación de la RV basada en vídeos de 360º mediante el cuestionario de presencia, la encuesta sobre el mareo por simulación y la comparación de los resultados con la bibliografía anterior. El método obtuvo una alta puntuación en el cuestionario de presencia y sólo un pequeño porcentaje de los participantes se detuvo prematuramente. Por lo tanto, la metodología de investigación es útil para los experimentos de comportamiento cruzado. Esto fue congruente con nuestros hallazgos en *el capítulo 4*. La metodología de RV basada en vídeos de 360º se percibió como realista. Además, casi todos los participantes terminaron el experimento sin ningún síntoma significativo de mareo por simulación. Esto es comparable con los resultados de un estudio anterior en el que se investigaron las intenciones de cruce de los peatones, lo que confirma la idoneidad de la metodología de RV basada en vídeos de 360º como metodología de investigación para estudiar las intenciones de cruce de los ciclistas. La metodología de investigación de la RV inmersiva también se utilizó y evaluó en *el capítulo 5.* En términos de realismo, las puntuaciones en la escala de presencia son buenas en general, excepto en la calidad de la interfaz. Las puntuaciones en la escala de miseria fueron buenas y mostraron que los participantes experimentaron, como mucho, vagos síntomas de mareo por simulación. En su mayoría, no se experimentó ningún síntoma. En general, se puede concluir que este tipo de realidad virtual resultó ser útil para este tipo de estudios.

Conclusión

Esta tesis ha contribuido a la comprensión del comportamiento de cruce de los VRUs cuando interactúan con los AVs y de los mecanismos subyacentes del comportamiento de cruce. Los factores pertenecientes a cada uno de los tres componentes (es decir, los vehículos automáticos, los vehículos de motoristas y la infraestructura), que juntos forman la interacción, son relevantes. Los resultados presentados muestran que los vehículos automáticos no tienen ningún efecto sobre el comportamiento de los peatones al cruzar la carretera a corto plazo. Sin embargo, esto depende de que los vehículos automáticos se comporten de acuerdo con las expectativas de los usuarios. Desde el punto de vista psicológico, los AVs afectaron a los VRUs pero no se tradujo en una adaptación del comportamiento. Los constructos psicológicos que se mostraron afectados por los AVs, fueron el control conductual percibido, la confianza en los AVs, el riesgo percibido y la familiaridad con los AVs. Los resultados de esta tesis muestran que los factores del vehículo, en particular la distancia entre el AVs y el VRU (es decir, el tamaño del hueco), fue el factor más importante que afectó a las intenciones de cruce de los VRUs a corto plazo. Las señales de movimiento de los vehículos tuvieron un mayor efecto sobre el comportamiento de cruce en comparación con los factores de automatización. Las VRUs son capaces de tomar decisiones de cruce basadas en las señales de movimiento del vehículo, posiblemente debido a sus estrategias de cruce de carreteras preaprendidas.

En esta disertación se utilizaron vídeos de 360° y tecnologías de realidad virtual inmersiva, así como cuestionarios para estudiar las intenciones y el comportamiento de los peatones y ciclistas al cruzar la calle cuando interactúan con los AVs. Los tipos de RV empleados durante los experimentos presentados funcionaron adecuadamente y muestran que este tipo de metodología es útil para encontrar factores y tendencias relevantes que también podrían encontrarse en el mundo real. Sin embargo, es necesario investigar más sobre la transferibilidad de los resultados.

Esta disertación ha contribuido a la creciente literatura sobre las interacciones entre los AVs y los VRUs, pero todavía se necesita más investigación. Las recomendaciones para futuros trabajos basados en esta disertación son las siguientes. La investigación futura podría investigar los efectos de la edad, el nivel educativo y las diferencias culturales y centrarse en una mayor variedad de comportamientos y cómo se ven afectados por los AVs. Se necesita más investigación para identificar cómo se comportan los AVs y cómo esto podría afectar al comportamiento de los VRUs. Los trabajos futuros deberían intentar centrarse más en responder a la pregunta de cuándo se deben utilizar los eHMI y cuándo no.

La investigación se realizó en un entorno controlado y los escenarios incluidos fueron limitados. Esto hace que la transferibilidad de mis resultados a la práctica sea limitada. Sin embargo, se pueden mencionar algunas implicaciones para la práctica. Hay que animar a los municipios a que pongan en marcha proyectos piloto que incluyan AVs y que también se centren en el estudio de las interacciones entre los VRUs y los AVs. Las interfaces hombre-máquina externas (eHMI) deberían utilizarse con cuidado. Los fabricantes de vehículos deberían considerar el uso previsto del vehículo antes de hacer un uso a gran escala de eHMIs específicas. Se recomienda también desarrollar señales de movimiento específicas de los vehículos que dejen claras las intenciones del vehículo. Por último, la información y la educación hacia los VRUs no sólo deberían centrarse en las capacidades de los AVs, sino también en las limitaciones.

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Chapter 1 - Introduction

Automated vehicles (AVs), also known as robocars, driverless, self-driving, or autonomous vehicles, are a new type of vehicles that will be on the road soon. AVs are a collection of driving automation systems that are designed to take over some or all of the driving tasks from drivers. Ultimately, these vehicles maybe able to perform driving tasks without a human driver. However, the other road users will still consist of humans who will have to interact with AVs. Pedestrians and cyclists will still be part of the traffic system. They will have to share the road with other vehicles that could be automated. In these situations, the pedestrians and cyclists might not be able to communicate with a driver and they might have to resort to a different manner of road negotiation. How will such interactions look like? Will they differ fundamentally from interactions with traditional vehicles? To answer these questions, it is important to note that there is not one type of AVs. There are different levels of AVs, each with their own capabilities and limitations as well as different external appearances. Pedestrians and cyclists might interact in different ways with various versions of AVs such as automated passenger cars with a driver and automated shuttles without a driver.

1.1 Vehicle Automation

AVs' appearances range from a similar appearance to that of a contemporary vehicle to a futuristic shuttle bus. To automate the driving tasks, AVs make use of sensors, such as cameras, radar, and laser scanners. The driving tasks range from adaptive cruise control used to control the speed and headway of the longitudinal driving direction to driving and interacting with other road users in all sorts of driving maneuvers without the need for human intervention. To distinguish the different levels of automation, a taxonomy system containing six levels has been proposed by the Society of Automotive Engineers (SAE International, 2018). A vehicle without any form of automation – this includes vehicles with assistance systems, such as lane keeping and blind spot warning – are considered to have a level 0 automation and are not considered as AVs. Level 1 and 2 AVs can perform limited driving tasks (i.e. steering and/or adapting speed) in automated mode, but the human driver always needs to supervise the vehicle and to be able to intervene when needed. It is important to note that the human is always considered to be the driver in these lower levels of automation even when the vehicle is performing certain tasks in automated mode. This is not the case for level 3 AV. The vehicle controls the entire dynamic driving task (DDT) on a sustained basis when in automated mode, but it can request the human to take over the driving task if needed. No human driver is considered to be needed at a level 4 AV within its operational design domain (ODD). A level 4 an AV can operate all the dynamic driving tasks, even in emergencies, without the need of a human. However, just like the previous 3 levels, the ODD in which a level 4 AV can operate is still limited. In contrast, a level 5 AV can perform all the driving tasks everywhere and anytime without the need of a human driver. However, whether, how and when a level 5 AV will become available, is part of an ongoing discussion.

Vehicles with different levels of automation have different capabilities and limitations and could, thus, have different possible impacts on traffic efficiency, safety and the environment. For example, these vehicles could drive closer to their predecessors, especially if combined with communication, and therefore increase the capacity of the road network. This also leads to a reduction in emissions since they experience lower air resistance when driving closer to their predecessors (Milakis, Van Arem, Van Wee, & Arem, 2017). However, AVs with a high level of automation might drive more often and more kilometers as there is no need for a driver and therefore cancel out the expected advantages. Also travel time utility (i.e. the perceived usefulness of time while traveling) can be affected, since highly automated vehicles may increase the amount of activities passengers can perform while traveling. Without the need for a driver, humans may choose to work and sleep in their vehicles. So, travelling for longer periods of time in an AV may be less inefficient compared to travelling in a non-automated vehicle. This could have implications for the commuting distance individuals chose to have.

Finally, and this is the focus of this dissertation, AVs will also affect traffic safety. AVs' sensors can operate much faster than humans can. Not only are they faster but they are also not affected by distractions, fatigue or drugs, amongst other things. Therefore, AVs could increase traffic safety (National Highway Traffic Safety Administration & Administration, 2013). However, the high expectations of AVs regarding traffic safety still need to be proven (ETSC, 2016; ITF/OECD, 2018). Most research focus on the effects of AVs on drivers and it has been shown that drivers have difficulties supervising AVs of low automation level for long periods of time, especially when the task is monotonous (Kyriakidis et al., 2017; Merat & De Waard, 2014; Saffarian, de Winter, & Happee, 2012). In addition, drivers may have a false sense of trust in the capabilities of their AV (Farah, et al., 2020). Therefore, drivers may not be able to react quickly enough or intervene in a safe manner when needed. An ineffective interaction between drivers and AVs may thus reduce the positive effect AVs have on traffic safety. So far, the first statistics of automated vehicles accidents have not shown an improvement of traffic safety as compared to non-automated vehicles (Biever, Angell, & Seaman, 2020; Schoettle & Sivak, 2015). Furthermore, fatal accidents of AVs have already been recorded (Biever et al., 2020). Drivers are not the only humans within the driving system and thus not the only ones who will be affected by changes produced by these vehicles. Pedestrians and cyclists have to negotiate with other road users while traveling, too. The changes implemented to the road traffic system by AVs could as well affect the pedestrians and cyclists.

1.2 Automated Vehicles & Vulnerable Road Users

Nowadays, worldwide 26% of road user deaths are pedestrians and cyclists. In Europe, 32% of the fatalities in traffic are pedestrians and cyclists (World Health Organisation, 2018b). The majority of cyclists' and pedestrians' casualties occur on urban roads and are a result of collisions with passenger cars (Adminaité-Fodor & Jost, 2020). In the Netherlands, where most of the research in this thesis was conducted, 42% of the road deaths are pedestrians and cyclists. The majority of these fatalities being cyclists (34%) which is much higher than in other countries (SWOV, 2019; World Health Organisation, 2018b). The Netherlands has a high number of cyclists and a high cycling mileage which explains why cyclists are highly represented in the statistics (De Groot-Mesken, Vissers, & Duivenvoorden, 2015). Pedestrians and cyclists do not have a shield that protects them, like car drivers, and have a low mass as compared to other road users. Therefore, they are considered vulnerable road users (VRUs; SWOV, 2012). Nonetheless, pedestrians and cyclists have their own characteristics such as their position on the road, their maneuverability, and speed of movement. For example, cyclists are more likely to share the road with, be overtaken by, and overtake motorized vehicles than is the case for pedestrians. This means that the exposure to a collision is different for cyclists as compared to pedestrians. Still, cyclists and pedestrians will both cross paths with motorized road users at intersections. The main cause of VRUs' fatalities are collisions with a motorized vehicle at an intersection in urban areas. AVs are expected to be able to react faster and more accurately due to their sensors and thus reduce the chance of a collision. However, AVs' drivers may be less attentive or occupied with other activities when not controlling the vehicle at certain moments removing the possibility for VRUs to communicate with a human. Whether communicating with a driver is needed for VRUs to interact safely with motorized vehicles remains an ongoing research topic (e.g. Amini, Katrakazas, & Antoniou, 2019). The negotiation of the road will still take place but it is unclear how this will happen and what the effects will be on the safety of VRUs. So, it is important that AVs are able to safely interact with VRUs to decrease the fatalities and injuries among pedestrians and cyclists. The challenges for AVs will be to detect the VRUs and their intentions and to interact with them safely.

The main aim of this dissertation is to understand the behavior of pedestrians and cyclists when interacting with an AV. The role of AVs' physical appearance, driver presence, and the presence of communication interfaces were investigated in this dissertation. AVs' physical appearance and driving style may differ from contemporary vehicles. For example, sensors placed on the roof of the vehicle could characterize the automated nature of vehicles. This could enable VRUs to recognize them as such and behave differently when they know they are interacting with AVs. How VRUs may change their behavior and what the impact could be on traffic safety are knowledge gaps that are scarcely being studied at the moment. Automation could make it possible for vehicles to operate without (attentive) drivers, but whether the lack of the possibility to interact with a driver affects VRUs behavior is unclear.

1.3 Focus and Scope of this Dissertation

Urban areas and, more specifically, intersections are the most dangerous locations for the interactions between VRUs and motorized vehicles. In addition, crossing the road is the most risky maneuver because it could expose VRUs to motorized vehicles (AVs or conventional vehicles (CVs)) directly. Therefore, this dissertation will focus on crossing behavior in urban areas. The manner in which the VRUs cross the road when interacting with AVs compared to when interacting with CVs can reveal how VRUs perceive them and adapt their behavior. Currently, AVs that are operating on public roads are scarce. In addition, performing a road crossing experiment in the field would have caused practical and ethical difficulties. Therefore, the empirical studies performed for this dissertation were performed using virtual reality. This dissertation aims to investigate the effects of AVs on pedestrians' and cyclists' crossing behavior in urban areas. Therefore, the following main and sub research questions have been defined:

To what extent do AVs affect the crossing behavior of pedestrians and cyclists?

1. What are the underlying factors that determine vulnerable road users' crossing behavior when interacting with an AV and how could AVs affect these factors and VRUs crossing behavior?

2. How do the physical appearance and eHMI of an AV affect pedestrians' crossing intentions in comparison to vehicles' motion cues and psychological factors?

3. How does the physical appearance of an AV affect cyclists' crossing intentions in comparison to vehicles' motion cues and psychological factors?

4. How does the presence and attentiveness of drivers in an AV affect pedestrians' crossing behavior in comparison to vehicles' motion cues and psychological factors?

5. How does Virtual Reality perform as a research method in terms of realism, validity and ease of use?

These research questions were investigated in empirical studies and are presented in *Chapters 3*, *4*, and *5* of this dissertation. In *Chapter 2* a theoretical framework was developed based on the literature on VRUs crossing behavior. It was important to identify which underlying factors are of interest and importance to VRUs crossing behavior in order to include them in the experiments to be designed. Therefore, a theoretical framework containing the relations between factors was useful as it provided insights on how AVs could affect VRUs.

In *Chapter 3*, a virtual reality crossing experiment for pedestrians was created to answer research question 2. The physical appearance of the vehicle and eHMIs effects on the VRUs crossing intentions were assessed as well as their effect on psychological factors. Vehicles' motion cues were included and their effect on the pedestrians compared with the effects of physical appearance of the AV and eHMIs. In addition, the realism, validity and ease of use of our developed methodology was assessed to answer research question 5.

In *Chapter 4*, the methods used in *Chapter 3* were reproduced but now for cyclists to answer research question 3. Again, the physical appearance and vehicles' motion cues were of interest for this study. The effects of the vehicle factors on crossing intentions and psychological factors were studied. The performance of the methodology was assessed in this chapter too.

Finally, in *Chapter 5*, a new method to study the crossing behavior of pedestrians was developed to answer research question 4. The driver's condition was included in this study as well as motion cues of the approaching vehicles and their effects on crossing behavior. Also psychological factors were investigated. This new method was assessed also.

1.4 Theories & Methods

A theoretical framework was developed (*Chapter 2*) to answer the research questions mentioned in chapter 1.3 and can be seen in figure 1. The framework consists of the interaction between AVs, VRUs and the infrastructure. The AVs, VRUs and the infrastructure are the three main components identified. Within each component categories were created to organize factors that should be investigated. In the case of AVs, a distinction was made between factors that belong to automation and factors that belong to the vehicle. Automation factors are AV characteristics that can be expected to come with automation and would be atypical for non-automated vehicles at the moment. An example of such a characteristic would be the absence of a driver. Factors that are considered to play a role with vehicles regardless of automation are included as vehicle factors, such as the speed of the vehicle. In the case of VRUs, special attention was given to psychological factors such as trust and expectations. These psychological factors could help explain how VRUs behavior would be affected by the other factors. When it comes to the infrastructure, I focused on the road design characteristics such as the right of way. The theoretical framework provided a theoretical basis for my studies. All the mentioned elements were carefully considered and included in the empirical studies to examine their role within the interactions. Psychological factors were carefully selected based on their relevance and ability to give insights in whether and how the VRUs adapt their behavior when interacting with AVs. The theoretical model is an adapted version of the Theory of Planned Behavior (TPB; Ajzen, 1985, 1991). TPB is one of the most frequently used models in psychology to explain how behavior emerges. TPB explains that the personal characteristics affect one's attitudes, social norms and perceived behavioral control towards a specific behavior- in this case crossing behavior. These three factors affect one's crossing intentions which in turn affects one's crossing behavior. The perceived behavioral control (i.e. perception of how successful one will be performing the behavior) is the only factor that can affect the crossing behavior directly, according to TPB. However, this model does not contain all the factors associated with the interactions between VRUs and AVs. It is hypothesized that the expectations VRUs have of AVs could also affect their behavior. For example, it is likely that VRUs that do not expect AVs to be safe, will behave differently than VRUs who expect AVs to be safer than human drivers. Furthermore, trust in AVs is assumed to play a role in how VRUs will behave and a correlation could exist between trust and expectations. Finally, the behavior of VRUs is expected to change as VRUs are exposed more frequently to AVs over time. VRUs are also assumed to adapt their behavior to specific situations. For that adaptation to take place a learning effect is needed and should, therefore, be taken into account and added to the theoretical framework. The theoretical framework (*Chapter 2*) serves as a theoretical basis for the empirical studies reported in *Chapters 3*, *4* and *5*.

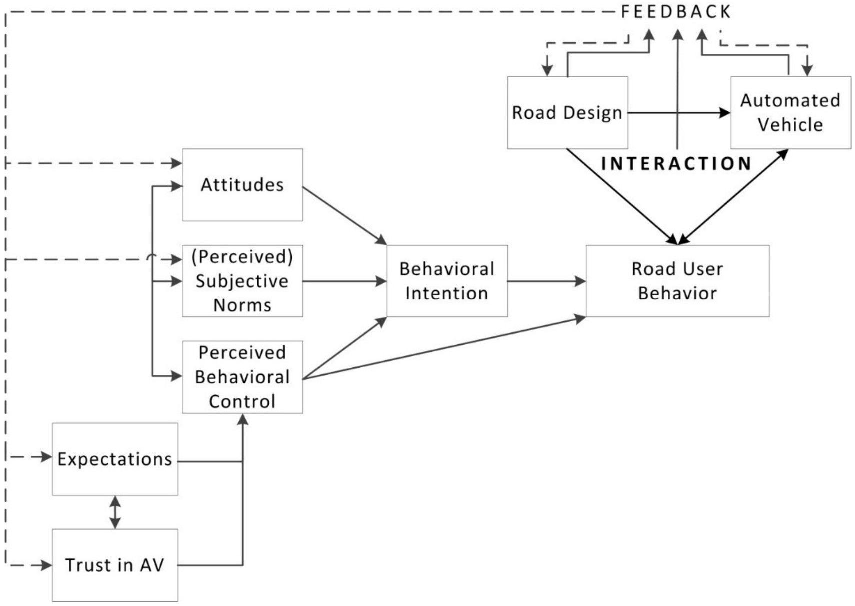

Figure 1. Our theoretical framework as proposed in Chapter 2.

Performing a crossing study with AVs in real life was a difficult feat when this research was conducted, and still is, as the number of AVs on the road is limited and letting participants cross the road came with ethical considerations. Therefore, a combination of different methods was used in the empirical studies. The methods used were virtual reality crossing experiments and surveys. Virtual reality (VR) was used to provide observational data on crossing intentions and crossing behavior. VR allowed to design a crossing experiment in which individuals crossed the road in a repeatable, and controllable manner without exposing them to any risk, such as a collision with a vehicle. In addition, it allowed to deploy and manipulate AVs for the experiments in a manner that would not have been possible in real-life due to practical, ethical, and financial reasons. For example, I was able to manipulate the vehicles digitally by adding a communication interface or by changing the physical appearance of the vehicle. Due to the simulated nature of VR, it was possible to present the conditions and scenarios created in exactly the same manner to all the participating individuals. In this research, two types of VR methods were used. First, the developed 360° smartphone-based VR. This VR set-up revolves around the use of videos which have been captured by a camera that has a field of view of 360°. These videos were then presented with the use of a smartphone that serves as the screen of a head-mounted display. The advantage of this type of VR method is that it uses videos recorded in real-life in contrast to computer simulated image. However, as the videos are pre-recorded there is no possibility to interact. Thus, instead of crossing behavior, the intention to perform a behavior was measured. The other type of VR set-up employed, is immersive computer simulated VR. This type of VR method allows individuals to move and act as they see fit. Therefore, road user behavior can be closely observed. Objective crossing intentions and behavioral data were captured with these two types of VR method environments.

The surveys allowed to investigate underlying psychological processes that influence behavior of individuals. Similar to VR, surveys allowed to collect information of the participating individuals in a controllable and repeatable manner. The data gathered using surveys was the following: demographics, trust in automation, perceived behavioral control, presence (i.e.

perceived immersion) in VR, and severity of simulation sickness symptoms. These variables were found to be the most important factors regarding the interactions between AVs and VRUs (as can be seen in *Chapter 2)*. All in all, the two VR methods in combination with the employed surveys facilitated capturing objective and subjective data to investigate the mechanisms of pedestrians' and cyclists' crossing behavior when interacting with AVs.

1.5 **Outline of this Thesis**

This dissertation consists out of six chapters and is organized in four parts: The introduction (this chapter) and the theoretical framework (*Chapter 2; Research question 1*), the empirical studies (*Chapters 3*, *4*, & *5; Research questions 2 - 5*), and the discussion and conclusions of this dissertation (*Chapter 6*).

Chapter 2 presents a theoretical framework based on psychological theories that are deemed relevant when studying interactions of road users. Furthermore, the state of the art about the interactions between VRUs and AVs is presented. It identified the knowledge gaps that need to be addressed for a better understanding of VRUs' behavioral adaptation when interacting with AVs.

Chapters 3 and *4* present empirical studies on crossing intentions of pedestrians and cyclists when interacting with an AV. The method used in both studies was 360° smartphone based virtual reality. In both studies, the physical appearance of the AV was tested as a factor alongside the psychological factors and motion cues of the vehicle. In *Chapter 3*, the effect of eHMIs on pedestrians' crossing behavior was investigated too. The performance of this newly developed type of VR as a research method was tested in both studies.

Chapter 5 presents an empirical study on the crossing behavior of pedestrians when interacting with an AV. The method used was again VR, but more specifically it was a computer simulated VR. This allowed to study the crossing behavior and validate previous findings on crossing intentions of pedestrians investigated in *Chapter 3* using the 360° smartphone based virtual reality. The automation factors that were investigated within this chapter were: the presence and the attentiveness of the driver. In addition, psychological factors and the motion cues of the vehicles were included. The performance of the VR method was tested and compared with the performance of 360° smartphone based virtual reality.

Finally, *Chapter 6* ends with the discussion and conclusions based on this thesis. The main findings are presented and the research questions are answered. Furthermore, the implications on the findings and the limitations of this thesis are discussed from a scientific as well as a practitioners' point of view. Recommendations for practice and future research are provided.

Chapter 2 - Interactions between Vulnerable Road Users and Automated Vehicles: A Synthesis of Literature and Framework for Future Research[1]

Abstract

Partially and fully automated vehicles (AVs) are being developed and tested in different countries. These vehicles are being designed to reduce and ultimately eliminate the role of human drivers in the future. Most fatal accidents of vulnerable road users (VRUs), pedestrians, cyclists and mopeds, involve a motorized vehicle. In addition, most of the accidents involving VRUs and motorized vehicles happen at road crossings. By replacing human-driven vehicles with automated vehicles, the human role will be altered and reduced which could lead to an increase in traffic safety. However, drivers are not the only ones who will have to adapt to automated vehicles, other road users, such as pedestrians and cyclists, will have to interact with vehicles with various levels of automation, too. Pedestrians and cyclists will still be humans and might behave in an unpredictable manner which could lead to unsafe behaviors. The main goal of this paper is to propose a theoretical framework which describes the interactions between automated vehicles and road user behavior under different road design conditions. This is a prerequisite to understand how to design safe urban environments where VRUs and automated vehicles can interact safely. A synthesis of the existing literature about the interactions between automated vehicles and VRUs, and the main factors that could influence VRUs' behavior is presented. The results of the synthesis and the identified knowledge gaps are discussed. Based on this, a theoretical framework for the interactions between VRUs and automated vehicles is developed and discussed.

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[1] This chapter is an adapted version of the following published article: Núñez Velasco, J. P., Farah, H., van Arem, B., & Hagenzieker, M. P. (2016). Interactions between Vulnerable Road Users and Automated Vehicles: A Synthesis of Literature and Framework for Future Research. In Proceedings of Road Safety and Simulations Conference 2016.

2.1 **Introduction**

Automated vehicles (AVs), of different levels of automation, will have an impact on many aspects of the transport system, including traffic safety (Milakis, van Arem, & van Wee, 2015). The main argument used is that the occurrence of accidents is primarily attributed to human drivers' errors (National Highway Traffic Safety Administration, 2008) and by replacing human drivers with automated systems the amount of traffic accidents would decrease (Fagnant & Kockelman, 2015). However, the deployment of automated vehicles in traffic, and the developments towards higher levels of automation will be gradual, and therefore, human drivers will continue to play an important role. For example, when automated systems fail and the driver has to take over control, or when other road users, such as cyclists and pedestrians, interact with automated vehicles. How the other road users will be affected by automated vehicles is a knowledge gap that has until recently largely been neglected. Road users are, at this moment, able to communicate and express their intentions through non-verbal communication such as hand gestures, eye contact, nodding. AVs will, thus, have to use other methods to communicate with the non-automated road users.

In the literature few studies focused on the interactions between vulnerable road users (VRUs) and AVs. Cyclists and pedestrians are vulnerable, and have the most fatal casualties when involved in an accident with motorized vehicles (Vissers, van der Kint, van Schagen, & Hagenzieker, 2016). Therefore, they should be taken into account when designing and deploying AVs. VRUs could experience confusing situations when they interact with AVs due to possible discrepancies between their expectations from AVs and the actual behavior of AVs. Blau (Blau, 2015) studied whether VRUs would adapt to AVs by changing their behavior. He used a survey in which he asked the participants about their stated-preference about road crossing facilities. The results indicate that AVs increased the preference for using bicycle and pedestrian crossing facilities, which could indicate that VRUs do not feel safe around AVs. This finding seems in contrast with what Núñez Velasco et al. found (Núñez Velasco, Rodrigues, Farah, & Hagenzieker, 2016). In this study, the researchers used a questionnaire and a focus group to study VRUs perceived safety of AVs. They found that cyclists indicated to feel safer interacting with an AV than with a traditional vehicle but only at unsignalized intersections. Pedestrians did not report differences in perceived safety. The contradicting findings of these two studies could be associated with the physical presence of an AV. While in the study of Núñez Velasco et al. (Núñez Velasco et al., 2016) AVs were actually operating in the study area, in Blau's research no AV was present in the vicinity. This could have affected the perception of the VRUs. Another study that found similar results as Blau et al. was performed by Hagenzieker et al (2016). In their study, a photo experiment, indicated that VRUs were conservative about the performance of AVs, perhaps pointing towards a conservative disposition towards AVs (M.P. Hagenzieker et al., 2016). Another study on VRUs and automated vehicles was performed, but instead of photos, the researchers used virtual reality assuming it to be a more realistic experience. The researchers presented a crossing scenario with different gaps and non-automated and automated vehicles to their participants (Farooq, Cherchi, & Sobhani, 2018). Their findings showed that cycling males preferred to interact with AVs rather than with traditional vehicles. The photo and VR studies (Farooq et al., 2018; M.P. Hagenzieker et al., 2016), no clear assessment of the realism of the study was taken, which is one of the main drawbacks of stated preference studies, thus the results should be compared with results from studies performed in a more realistic setting.

Field experiments on the interactions between VRUs and AVs have also found conflicting results. Lundgren et al. used a vehicle with the steering wheel on the passenger side to simulate interactions between a pedestrian and an AV, a so called wizard of Oz technique (Lundgren et al., 2017). A fellow researcher sitting on the driver side would behave in ways which could become possible once the vehicle is automated, such as reading a newspaper and talking on a phone. The results showed that pedestrians decided to cross the road less often when the ‘driver’ seemed distracted. In addition, the pedestrians experienced the interactions with an inattentive driver as more unpleasant. However, the participants had no reason to expect the vehicle to be automated as they were not told this. Thus, their behavior could have been triggered by a distracted driver and not the interaction with an automated vehicle. In a similar study by Rodríguez Palmeiro, et al. crossing situations with a traditional and an automated vehicle were simulated using the Wizard of Oz technique (A. Rodríguez Palmeiro et al., 2018). This study varied the speed profile of the approaching vehicle, the presence of labels indicating the vehicle to be automated, behavior of the driver (attentive of distracted), and yielding behavior of the vehicle, resulting in 20 scenarios. The participants had to indicate when they thought that it was safe to cross, as well as the last moment they would have crossed. No differences were found between the scenarios, non-AV and AV, indicating that the ‘automated’ vehicle did not change the crossing intentions of the participants. However, these results could be biased by the fact that pedestrians were not allowed to execute their crossing decision out of ethical reasons. Rothenbücher et al. also used the Wizard of Oz technique to let other road users believe the vehicle was not being driven by anyone. They drove in two areas where they expected VRUs to have to interact with the vehicle. They found that their driverless ‘AV’ did not have an effect on pedestrians’ crossing behavior except when it misbehaved (e.g. drove in to the zebra crossing when the pedestrians were about to cross; Rothenbücher, Li, Sirkin, Mok, & Ju, 2016). Furthermore, the expectations and trust in the vehicle were studied. The participants seemed to use two concepts of expectations and trust, and thus reported to have low expectations and trust in contemporary AVs, but high expectations and trust in future versions. To summarize, findings point towards a conservative crossing pattern of VRUs even when it was explicitly stated that they were interacting with AVs. It could be that communication devices mounted on AVs indicating what the VRU should do, would affect VRUs’ behavior.

Merat et al. (Merat, Madigan, Louw, Dziennus, & Schieben, 2013) used a questionnaire to study the preference of how VRUs would like AVs to communicate with them, which were operating in the area. The participants were asked to indicate what information they would like to receive from AVs. Furthermore, the participants’ perceived safety was measured. The results indicate that the participants prefer to be informed whether they have been detected by the AV, but they are not interested in knowing the speed of travel of the vehicle. The results also indicated that perceived safety of AVs depends on the presence of road markings indicating where the vehicle will drive. Clamann et al. conducted a field test to study the effectiveness of communication methods of vehicles by using a display mounted on the front of a vehicle (Clamann, Aubert, & Cummings, 2017a). The researchers experimented with different sign designs, such as a ‘cross advisory’ and a ’don’t cross advisory’ indicating when the pedestrian can cross. Their participants had to report whether they would cross. The response time and safety of the pedestrians’ crossing behavior were analyzed. Their findings pointed out that contrary to the participants’ own beliefs, their decisions appeared to rely on past crossing behavior experience and that they did not make use of information provided by the AV. In another study, a real vehicle with a LED-strip mounted on the front window of a vehicle was used to communicate with the participants who were instructed to cross the street (Habibovic, Andersson, Nilsson, Lundgren, & Nilsson, 2016b). The results of this experiment showed that the participants experienced interactions with an AV with the LED-strip as more positive as compared to one without it. Finally, a study performed in virtual reality, assessed how simulating eye contact could affect VRUs' crossing behavior. The researchers placed eyes on the headlights of their AVs (Chang, Toda, Sakamoto, & Igarashi, 2017). The eyes of the vehicles made eye contact with the participant. The researchers found that their participants were able to make a crossing decision faster, with less errors, and that the participants felt safer when they were making eye contact with the vehicle. In conclusion, the presented studies show that people may like AVs that have a communication device, but that they nevertheless whether they use it to make a crossing decision remains inconclusive.

To summarize, limited studies have investigated the interactions between VRUs and AVs, and a (theoretical) explanation of how VRUs' would adapt and change their behavior is missing. This study will fill this gap by proposing a theoretical framework explaining how VRUs' behavior could be influenced when they interact with AVs. The proposed framework, based on the Theory of Planned Behavior, aims to describe and explain how an AV will affect other road users' behavior when they both interact. Trust, feedback and expectations are included as well in the framework as these factors have been proven to affect road users' behavior. This framework is aimed to create more insight in how road users' behavior could change due to AVs' characteristics.

In the following sections a synthesis of research literature and useful models and concepts will be presented, followed by identified knowledge gaps, and the proposed theoretical framework. Finally, the paper concludes with a discussion and conclusion.

2.2 Synthesis

This section discusses the theories and constructs behind the theoretical framework proposed in this study, and the argumentation for their choice. We will also review behavioral models of relevance in the context of cyclists' and pedestrians' behavior when interacting with AVs. These interactions could be in the form of crossing in front of the vehicles, in areas where they rarely or often will be present, will ride in the (lateral, frontal, etc.) proximity of AVs and, overtaking slow driving vehicles.

Our framework requires a model that facilitates the understanding and in a later stage predicts VRUs' behavior. It should, in addition, contain the constructs that have been proven to affect road users' behavior and constructs that could be relevant for the interactions between VRUs and AVs. This could provide the possibility to improve road users' behavior in a later stage. Their behavior could be improved through, for example, self-explaining road design addressing critical points in interactions between VRUs and AVs, educational programs addressing the proposed constructs (e.g. trust and expectations), or AVs communication design to interact with other road users.

A variety of models have been designed to predict behavior based on motivational constructs. These models propose sociodemographic mediator variables, such as age and gender, to explain the effects on behavior, and have been used in various health behavior studies (Panter, Griffin, Jones, Mackett, & Ogilvie, 2011; Parker, Manstead, Stradling, & Reason, 1992). Health Belief Model (Janz & Becker, 1984) is a motivational model that includes six determinants of behavior, such as Perceived Severity and Perceived Benefits. This model has been criticized because of its poor definition of constructs, low discriminant validity, and therefore poor predictive validity (Armitage & Conner, 2000). Similarly, the Protection Motivation Theory (Rogers, 1983), which contains two appraisal strategies - Threat appraisal and Coping appraisal also lacks predictive power (Armitage & Conner, 2000). Social Cognitive Theory (Bandura, 1986) accounts for one's confidence in successfully carrying out certain behaviors - self-efficacy - and the perception of effects out of one's control depending on the situation - outcome expectancies -. Self-efficacy, in particular, has been found to be a principal behavior predictor. However, only small to medium predicting effects have been found despite the central role of this predictor in the Social Cognitive Theory (Armitage & Conner, 2000). The Theory of Planned Behavior is also one of the motivational models. This theory is based on the Theory of Reasoned Action (TRA) (Ajzen, 1991). TRA was designed to understand and predict the behavior of individuals based on their intentions, which were affected by their attitudes and subjective norms. However, this model has been criticized for only being able to predict behavior that is volitional (Fishbein, 1993). Therefore, Perceived Behavioral Control was added to the model to create the Theory of Planned Behavior. From all of these four models, the Theory of Planned Behavior has been proven to be better at predicting road users' intentions and their behavior (Armitage & Conner, 2000). It has also often been used in traffic research (e.g. Evans & Norman, 1998), and for those reasons it has been chosen as a basis for the proposed framework.

The literature also contains other constructs that affect road users' behavior, which are not explicitly part of the Theory of Planned Behavior, and, thus, should be included. Research has demonstrated, for example, that expectations about the situation play a major role in road user behavior (Houtenbos, Jagtman, Hagenzieker, Wieringa, & Hale, 2005). Trust is a very important construct in human-machine interactions, which is the case when humans interact with AVs, (Madhavan & Wiegmann, 2007) . Behavioral adaptation (C.M. Rudin-Brown & Noy, 2002) could develop over time and take place when VRUs gain positive and negative experience with AVs. For behavioral adaptation to take place, a clear feedback loop is needed. Humans would need to learn to adapt. Lastly, demographic factors have also been related to road user behavior (Vissers et al., 2016).These constructs and theories, and the motivation for their choice, will be further explained in the following sections.

2.2.1 Theory of Planned Behavior

The Theory of Planned Behavior (TPB) is relevant for studying road user's behavior in their interactions with AVs as it can be used to understand and predict this behavior. Therefore, it can be used to guide interventions designed to increase road safety (Elliott, Thomson, Robertson, Stephenson, & Wicks, 2013). TPB has been widely used to predict behavior in different areas (for a review, see (Godin & Kok, 1996)). Several meta-analyses on TPB have confirmed the strong relationships between attitudes, social norms, and perceived behavioral control with behavioral intention (Armitage & Conner, 2001; McEachan, Conner, Taylor, & Lawton, 2011; Notani, 1998). The results of the meta analyses showed that the variance explained in intention by the three TPB variables was between 42% and 45% according to McEachan et al. (McEachan et al., 2011), and between 27% and 39% according to Armitage & Conner (Armitage & Conner, 2001). In addition, a review of the literature resulted in a mean correlation ranging between 0.59 and 0.66 between the TPB variables (attitudes, perceived social norms, and perceived behavioral control) and intentions (Ajzen, 2011).

TPB and TRA (Ajzen, 1991), both have behavioral intention as a central factor. The stronger the intention to perform a certain behavior, the more likely it is that the individual will perform it. In TRA the intention is predicted by attitudes and subjective norms (Ajzen, 1985). In TPB perceived behavioral control is added to the model, as can be seen in Figure 2 (Ajzen, 1991). Attitudes are defined as the positive or negative judgements of a certain behavior by the individual. Subjective norms are the perceived judgements of the behavior. Perceived behavioral control is the perceived ability to perform a behavior, and is a direct predictor of behavior. This is how TPB is able to predict non-volitional behavior in addition to voluntary behavior.

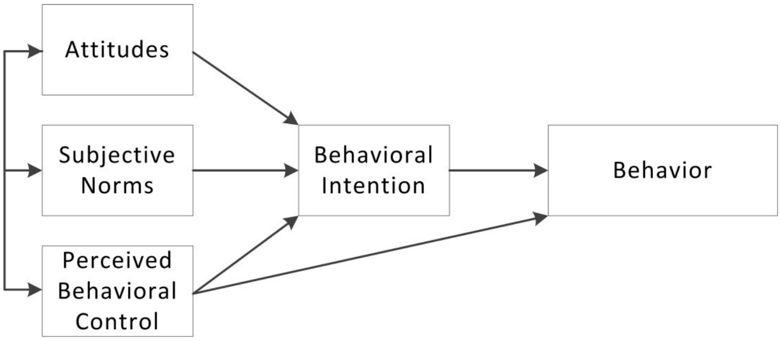

Figure 2. The Theory of Planned Behavior (Ajzen, 1991).

Evans and Norman (Evans & Norman, 1998) applied TPB to the prediction of crossing intentions of adult pedestrians. They expected that perceived behavioral control would be the main predictor. To test this they deployed a TPB questionnaire and four different scenarios. The participants had to read each scenario and then complete the TPB questionnaire, which contained questions about the attitudes, subjective norm, behavioral control, self-identity (*do you see yourself as a 'safe pedestrian*), and behavioral intention. They found that the TPB is able to explain between 37% and 49% of the variance in road crossing intentions. Perceived behavioral control was the strongest predictor, in line with previous studies on road safety behavior [18, 19]. This means that the chances of participants performing a certain behavior is higher if they think they can do it successfully. The limitation of these studies is that only stated intentions are measured. In addition, the limited number of items per scale are a limitation, although, the scales predict the behavioral intentions significantly.

A study on pedestrians' violations (Moyano Díaz, 2002) used TPB to predict the relation between intentions and reported violations. The researchers of this study found a significant fit for TPB constructs as predictor of behavioral intentions. In addition, they found significant high correlations between pedestrian behavioral intentions and reported violations which proves the ability of TPB to predict behavior. Research among college students (Jalilian, Mostafavi, Mahaki, Delpisheh, & Rad, 2015) also demonstrated the utility of TPB in predicting their crossing behavior. Jalilian et al. studied the safe road-crossings by creating and distributing a custom made TPB questionnaire. The researchers found significant correlations between the TPB factors, confirming that TPB can be used for research about crossing behavior. In addition, there have been studies about distracted pedestrians (Barton, Kologi, & Siron, 2016), adolescent pedestrians' intentions to follow the crowd in a risky road-crossing situation (Zhou & Horrey, 2010), child pedestrians railway-crossing violations (Darvell, Freeman, & Rakotonirainy, 2015), and pedestrian's intention to jaywalk (Xu, Li, & Zhang, 2013). When it comes to cyclists, there have been studies using TPB for predicting the intentions of wearing bicycle helmets (Lajunen & Räsänen, 2004; O'Callaghan & Nausbaum, 2006) and predicting the willingness to commute by bicycle (Lois, Moriano, & Rondinella, 2015). TPB research on VRUs' behavior when interacting with an AV has, for obvious reasons, not been performed.

TPB is criticized for depicting decision making as a rational process. Ajzen (Ajzen, 2011) explains that rational and/or flawless beliefs are not an assumption of the TPB. TPB focusses mainly on behavior aimed to achieve a goal, which is why it is misinterpreted as a rational process. In addition, TPB has been criticized for not being good enough to predict intentions and behaviors of human beings completely (Conner & Armitage, 1998) and it is unclear whether attitudes affect behavior or vice versa (Kroesen, Handy, & Chorus, 2017). Another critique often raised is the fact that TPB supposedly does not take affect and emotions into account. These critiques should be taken into account when working with TPB. As evaluations of TPB suggest that there is room for expansion of the model [9, 38], we see the need of adding the behavioral models and concepts, behavioral adaptation, trust, and expectations, to our framework in addition to TPB.

2.2.2 Behavioral Adaptation

Behavioral adaptation refers to “the collection of behaviors which may occur following the introduction of changes to the road–vehicle–user system and which were not intended by the initiators of the change” (OECD Scientific Expert Group, 1990). Thus, the road users must perceive the change in the system before they can start to alternate and learning their behavior. Risk homeostasis (Wilde, 1982) is an precursor of the behavioral adaptation concept .The main concept of risk homeostasis is that individuals target a certain level of risk. If their actual level of risk is lower than their preferred level of risk, then the individual will adapt his/her behavior in a way that increases the perceived level of risk. Some problems risk homeostasis encountered were being to general and not testable (Wilde, 1988). According to Ewing and Dumbaugh (Ewing & Dumbaugh, 2009), conventional traffic safety theories, that state that more ‘forgiving’ road designs only increase safety, do not account for the fact that human behavior can change too. By designing a road to be more forgiving towards road users, they are given the possibility to take more risks. This is what potentially causes an adverse effect. In addition, measures inside vehicles also elicit behavioral adaptation.

Research shows that driver assistance systems can lead to negative behavioral adaptation. Hoedemaeker and Brookhuis (Hoedemaeker & Brookhuis, 1998) noted that adaptive cruise control (ACC) was liked by the majority of participants in a driving simulator study because of its helpfulness. The participants took more risks when driving with ACC than they did without ACC in the form of smaller time headways, higher deceleration rate and higher speeds. A meta-analysis showed that different kinds of ACCs have different effects on behavior and that it may not be possible to conclude how ACCs in general will create behavioral adaptation (Dragutinovic, Brookhuis, & Hagenzieker, 2005). However, there seems to be a positive relation between the amount of support ACC provides and behavioral adaptation. Another review on psychophysiological effects of ACC and highly automated vehicles on drivers’ performance showed that there are some indications that heart rate is reduced by driving in an AV (De Winter, Happee, Martens, & Stanton, 2014). Not all studies included in the analysis reached the same conclusion, thus, no clear conclusion can be drawn without more research into this area. However, it is clear that drivers adapt to the system and that it does not necessarily increase safety (De Winter et al., 2014; Dragutinovic et al., 2005; Hoedemaeker & Brookhuis, 1998). These findings indicate how drivers adapt to AVs. The question remains on how VRUs will adapt to these vehicles over time. AVs could behave in a very defensive manner to increase the safety of an interaction with another road user. This could lead to a behavioral adaptation in the form of abuse of this defensive driving style. In addition, it is unclear how VRUs are going to adapt to the lack of eye contact.

Rudin-Brown and Noy presented a qualitative model (C.M. Rudin-Brown & Noy, 2002), in which behavioral adaptation of an individual depends on one’s personality, control seeking, one’s mental model, and trust. If an individual gets in contact with a change to one’s environment and learns new behavior through feedback, he or she will adapt his or her trust level. They tested this model in a number of driving simulator studies, and field tests on a track (Christina M Rudin-Brown & Parker, 2004). The conclusions drawn from these studies were that too much trust in a system induces risky behavioral adaptation, and particularly when this trust is false. In addition to trust, learning and feedback allow behavioral adaptation to occur and therefore need to be incorporated in our model.

Trust

Trust defined as “the attitude that an agent [in this case AVs] will help achieve an individual’s goal [in this case the VRU] in a situation characterized by uncertainty and vulnerability” (Lee & See, 2004) could be seen as a cause of road users’ behavior or an outcome of an interaction with AVs (Madhavan & Wiegmann, 2007). Many studies have been performed on the dynamics of trust. Hoff and Bashir (Hoff & Bashir, 2015), for example, proposed a model that represents 29 factors that influence trust, such as experience, attitudes, and understanding of the system. It explains how trust is affected by different factors depending on the kind of trust, and how the reliance on systems changes prior and during interactions. This model is not the only one with an extensive list of factors affecting trust. In a human-automation interaction trust influences the reliance on automation, but it does not determine it. Principally, trust influences reliance in situation where uncertainty is present and where resources to explore all alternatives are lacking (Lee & See, 2004).

During human interactions with a system, its performance is the most important factor affecting humans’ reliance. Muir (Muir, 1994) specifies how experience with a system changes trust. He concludes that a user can have appropriate (dis)trust towards an automation, if the user trusts automation and it is of high quality, but also if the user distrusts automation or when it’s of low quality. However, a user can also wrongly mistrust automation. Particularly, in cases where automation is wrongly mistrusted this can lead to accidents or inefficient interactions (Lee & See, 2004) in the case of AVs. Therefore, the trust people have in automation and their reliance on AVs must be taken into account in contemporary research on VRUs-AVs interaction and carefully examined.

2.2.3 Expectations

Expectations have been proven to be an important factor affecting behavior (Houtenbos, 2008; Theeuwes & Hagenzieker, 1993). Studies found that road users are quite good at adapting to unexpected situations, one of them is Houtenbos’ study. Houtenbos (Houtenbos, 2008) studied the interactions between car drivers at intersections, and provided insights on how expectations affect drivers’ interaction behavior. She proposed a framework which describes how drivers’ interactions depend on their expectations, information processing, (road) environment and interaction space. This framework provides insights on expected changes in behavior due to changes in expectations. Houtenbos’ framework takes into account the short and long term expectations (Knapp, 1998). Short term expectations are expectations that are enriched with the information one has at that particular moment, in addition to the long term expectations. Long term expectations are a priori ideas about certain situations, such as expectations about how the driving behavior of other road users will be on a highway. Expectations and reduction of uncertainty play a major role in “self-explaining roads” (Theeuwes & Godthelp, 1995), which is part of the Dutch road safety approach (Wegman, Aarts, & Bax, 2008). This way of designing roads is devised to increase road users’ performance by helping them forming accurate expectations . Research has shown that road users’ expectations, about how they should behave in a certain situation and road lay out, guides their behavior, whether they are correct or not (C. Rudin-Brown, Jonah, & Boase, 2013). Therefore, roads, including their specific design characteristics and the presence of various road users, should help road users create the right expectations so that they behave adequately. In TPB expectations are also important: Perceived behavioral control is one's expectation of the probability of performing a certain behavior successfully, which is closely related to "self-efficacy" (Bandura, 1986). We assume that perceived behavioral control is derived from general expectations about the situation. Thus, expectations should be part of our proposed framework and precede perceived behavioral control.

AVs could make VRUs create different expectations or change their expectations. For example, by using communication displays, the intent of the vehicle could be communicated to the VRU manipulating the VRU to behave in a manner that fits the situation. In addition, AVs are expected to behave more consistent as their behavior will be programmed, which would help VRUs to create more accurate expectations. However, VRUs could fail to create accurate expectations, for example, when different AVs use different signs to indicate the same intent, or when an AV is not recognizable as such.

2.3 Theoretical framework

The literature described in this paper gives insights into the knowledge gaps related to the interactions between VRUs and AVs, which are in line with previous reviews (Parkin, Clark, Clayton, Ricci, & Parkhurst, 2016; Vissers et al., 2016). TPB has been used in various traffic related studies but has not been used to investigate the behavior of road users interactions with AVs. In addition, the literature on road user behavior points out that also other factors influence road users' behavior. Studies have suggested that TPB can be expanded to increase its predictive validity. In addition, the short term and long term of the interactions need to be targeted by researchers. Behavioral adaptation could affect the road users' behavior and in that case, undermine the safety or efficiency of AVs. This can be related to differences in trust and expectations. Rothenbücher et al. found that a difference exists between trust and expectations now and in the future (Rothenbücher et al., 2016). More research is needed to understand how these constructs influence the behavior of the road users and thus the interactions with AVs and how these constructs are affected by AVs' characteristics, such as the driver absence, distinguishableness as an AV, communication capabilities, physical appearance and level of automation. In conclusion, some studies have already targeted the interactions between AVs and VRUs but many questions remain. Therefore, we propose a theoretical framework combining the literature on factors that influence road users' and TPB to better understand what the effects of AVs could be on road users' behavior.

Figure 3 presents our proposed theoretical framework, which combines TPB and constructs that affect VRUs' behavior and in which we assume will be relevant when studying the interactions between AVs, VRUs and road design. The core of this framework is the interaction of VRUs with AVs with various characteristics taking into account the environment in which they interact, in particular the road design. The characteristics of VRUs, AVs and road design that we think are important to be taken into account are as following:

(1) Characteristics of the road design: the number of lanes, type of intersections, presence of road signs, presence of crossing facilities for VRUs and communication capabilities of and to the road design.
(2) Characteristics of AVs: their programmed 'driving' behavior, communication capabilities with the road and other road users, presence of a driver, distinguishableness as an AV, and level of automation.

(3) VRUs' characteristics: mode of transport, a priori expectations, trust levels, and experience with AVs. Demographics, age and gender have also proven to correlate with certain behavior however, TPB assumes these factors affect the TPB constructs instead of directly having an effect on behavior.

Following our proposed theoretical framework, road users' behavior depends on their behavioral intentions and perceived behavioral control, which is adopted from the Theory of Planned Behavior (Ajzen, 1991). The behavioral intentions depend on the attitude towards the behavior, the perceived subjective norm and the perceived behavioral control, and these three factors also affect each other (Ajzen, 1991). We added the assumption that perceived behavioral control is affected by trust in AVs and by expectations about the situation in general, such as expectations about who has the right of way, trajectory and speed of the other road user, and about safety. Finally, we assume that the expectations are affected through feedback obtained from previous interactions, and by feedback provided by the road design and AVs. The effect feedback will have on behavior depends on the feedback's nature, such as amount, and intensity. VRUs are more likely to change their behavior if they receive a high amount of feedback, due to, for example, a high penetration rate of AVs. In addition, it is likely that VRUs change their behavior after an accident with an AV, which we see as an extreme form of feedback. Trust is, in this framework, assumed to have an effect of expectations, which have been created by the interactions through feedback, and a cause affecting behavior through influencing one's perceived behavioral control. Feedback of the interaction has a direct effect on expectations as the VRU uses this feedback to assess its performance and changes its expectations accordingly and on trust (Heikoop, de Winter, van Arem, & Stanton, 2015), but in the long term it will probably also have effects on attitudes, perceived subjective norms, AVs and road design. For the latter two it could come in the form of, for example, updates for AVs software and changes in the road design.

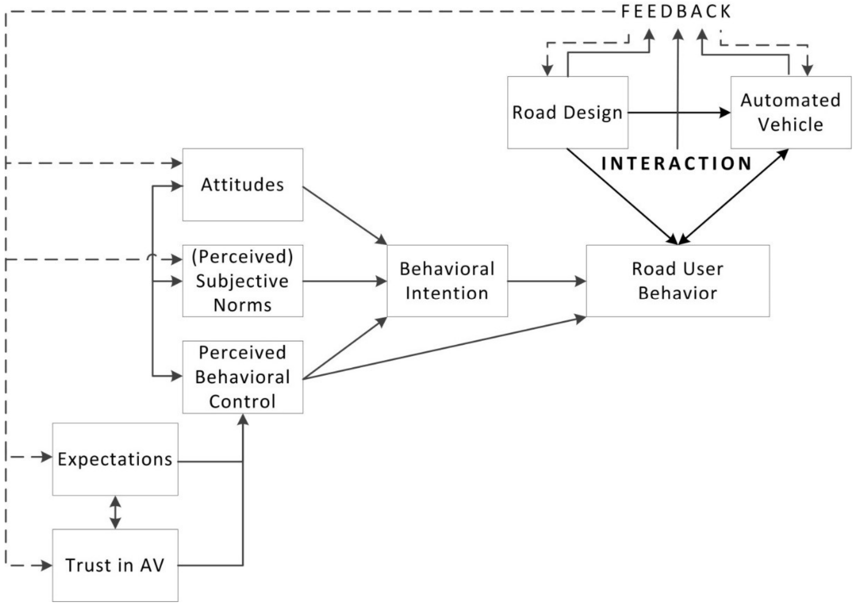

Figure 3: The proposed theoretical framework. The dashed lines represent how behavior could be affected after an indefinite number of interactions depending on the feedback's nature.

2.4 Discussion and conclusion

Our proposed theoretical framework is designed to provide a better understanding of the mechanisms that affect road users' behavior when interacting with AVs, and in a later stage predict road users' behavior in such interactions. We have chosen the TPB as a basis for our proposed theoretical framework and extended it by adding the constructs of trust and expectations as we assume that these affect the perceived behavioral control. In addition, a feedback loop resulting from the interactions has been added to the framework.

The proposed theoretical framework contains the dominant relations that affect behavior when a road user interacts with an AV. Future changes in road design and AVs could affect specific elements in our model, and the way our model performs. For example, if at some point communication capabilities are implemented that make it possible to communicate with road design, AVs, and other road users, a two-way arrow should be added to the model between 'road design' and 'road user behavior', and between 'road design' and 'automated vehicle'. Also, the penetration rate of AVs affects (the outcomes of) this model. If there are just a few AVs on the road it is possible that other road users do not interact frequently enough with AVs to learn from these interactions. If the penetration rate is high, and lots of AVs are on the road then the feedback would have more effect on road users' behavior. In contrast, software updates of AVs could influence, negatively or positively, the learnt behavior of road users, particularly when the updates would change AVs' behavior. For example, allowing less space between them and VRUs could result in a higher perceived unsafety by the VRUs. Further, not all road users have the same level of expectations and trust when they start interacting with AVs and thus this should be taken into consideration. Further research would be needed to investigate how feedback affects expectations and trust. As mentioned earlier, there are few studies on the interactions between VRUs and AVs, but none of these studies until now has focused on how VRU behavior would changes over time, and how this change in behavior is established, which is not surprising given that AVs are not common on the road yet.

In our following studies we will apply this model to explore its usability. Studies could include longitudinal experiments that investigate the changes in trust, expectations, TPB constructs and behavior over time with the help of, for example, questionnaires, video recordings and field tests.

Chapter 3 - Studying Pedestrians' Crossing Behavior when Interacting with Automated Vehicles using Virtual Reality[2]

Abstract

Partially and fully automated vehicles (AVs) are being developed and tested in different countries. These vehicles are being designed to reduce and ultimately eliminate the role of human drivers in the future. However, other road users, such as pedestrians and cyclists will still be present and would need to interact with these automated vehicles. Therefore, external communication interfaces could be added to the vehicle to communicate with pedestrians and other non-automated road users. The first aim of this study is to investigate how the physical appearance of the AV and a mounted external human-machine interface (eHMI) affect pedestrians' crossing intention. The second aim is to assess the perceived realism of Virtual reality based on 360° videos for pedestrian crossing behavior for research purposes. The speed, time gap, and an eHMIs were included in the study as independent factors. Fifty-five individuals participated in our experiment. Their crossing intentions were recorded, as well as their trust in automation and perceived behavioral control. A mixed binomial logistic regression model was applied on the data for analysis. The results show that the presence of a zebra crossing and larger gap size between the pedestrian and the vehicle increase the pedestrian's intention to cross. In contrast to our expectations, participants intended to cross less often when the speed of the vehicle was lower. Despite that the vehicle type affected the perceived risk of the participants, no significant difference was found in crossing intention. Participants who recognized the vehicle as an AV had, overall, lower intentions to cross. A strong positive relationship was found between crossing intentions and perceived behavioral control. A difference in trust was found between participants who recognized the vehicle as automated, but this did not lead to a difference in crossing intentions. We assessed the research methodology using the presence questionnaire, the simulation sickness survey, and by comparing the results with previous literature. The method scored highly on the presence questionnaire and only 2 out of 55 participants stopped prematurely. Thus, the research methodology is useful for crossing behavior experiments.

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[2] This chapter was first published: Núñez Velasco, J. P., Farah, H., van Arem, B., & Hagenzieker, M. P. (2019). Studying pedestrians' crossing behavior when interacting with automated vehicles using virtual reality. Transportation research part F: traffic psychology and behaviour, 66, 1-14.

3.1 **Introduction**

Taking the control of vehicles from human drivers, who by their nature make mistakes, and handing it over to automated vehicles (AVs), which are believed to be accurate and reliable, could, in theory, increase traffic safety. There is potential for AVs to prevent accidents by tackling the cause of these accidents (e.g. speeding) but, they could also cause accidents that are not occurring at this point, such as accidents caused by a failed transition of control from the AV to the driver (ETSC, 2016). Crash data available of AVs has failed to prove a decrease of crashes made by AVs as compared to contemporary vehicles (Schoettle & Sivak, 2015). Acquiring enough data to investigate AVs performance based on their crash data may not be practical for an ex-ante assessment (Kalra & Paddock, 2016). To diminish the amount of accidents to zero the whole system must be improved. In other words, automating the vehicles is not enough. The interactions of AVs and other road users must happen in a safe and efficient way too to ensure a reduction of crashes. Therefore, we will study the interactions between AVs and other road-users.

It is of importance that AVs can cope with vulnerable road users (VRUs) and that VRUs understand how to behave in these interactions to increase traffic safety. In Europe, most of the VRUs' fatalities happen in collisions with motorized vehicles (Adminaite, Allsop, & Jost, 2015). Most of the collisions take place at an intersection. Cyclists and pedestrians are considered vulnerable as compared to the motorized road users because they lack a metal shield to protect them. VRUs interact frequently with other road users at intersections when crossing. Therefore, this paper studies crossing behavior of pedestrians in front of an AV.

In the literature, field road crossing experiments can be found that examine the interactions between AVs and pedestrians by having participants experience a crossing situation (Clamann, Aubert, & Cummings, 2017b; Habibovic, Andersson, Nilsson, Lundgren, & Nilsson, 2016a; A. Rodríguez Palmeiro et al., 2018; Rothenbücher et al., 2016; Vissers et al., 2016). For example, Rothenbücher and colleagues (2016), made use of a vehicle that appeared to be driverless ("ghost driver") by hiding the driver "inside" the driver's seat and by attaching LIDAR, radar, stickers that read "Stanford Autonomous Car", and other equipment on the vehicle. The locations chosen for the experiment contained a pedestrian crossing and a roundabout. The people who interacted with the vehicle did not know anything about the experiment and their behavior was recorded on video. The authors found that this driverless looking vehicle did not significantly change the way people interacted with it, except when the vehicle malfunctioned by making uncontrolled movements. In these cases, people hesitated to cross or wait for the vehicle to make the first move. In two other studies participants were confronted with an inattentive driver. In a controlled field experiment by Lundgren et al. (2017) the participants reported in a questionnaire being less willing to cross when the driver was looking forward, reading the newspaper or sleeping than when the driver made eye contact with them. However, the sample size of this experiment was relatively small (N = 12), and no statistical tests were conducted to verify the results. Rodríguez Palmeiro et al. (2018) measured the smallest gap between the participant and the vehicle that would be accepted by the participant to cross (their willingness to cross). The results showed that the participants' willingness to cross did not seem to be affected by the fact that the driver was distracted and that the vehicle had stickers that read "Self-driving". It is interesting to note that the participants *reported* that their crossing intention was affected by the driver's state and the vehicle appearance although this was not supported by the findings regarding the accepted gaps measured in the field test. These studies suggest that vehicle appearance has an insignificant effect. Another possible explanation for these results, is that the participants were not immersed enough in the experiment and therefore did not perceive any danger, hurry, or need to cross.

When confronted with a communication display on the car, studies have found contrasting results. Fridman et al. (2017) assessed 30 communication displays by using an online survey. Text, projections on the floor in front of the vehicle, conventional traffic signs, and colored headlights are some examples of the different designs that were tested. The participants had to imagine they were about to cross and the vehicle that was at the intersection was communicating with them using a communication display. They were requested in each scenario to indicate whether they thought it would be safe to cross or not. In none of the tested scenarios all of the participants decided to cross. The five designs which showed the highest agreement between intent and participants' decisions contained words (i.e. walk) or consisted of conventional traffic signs. So, the communication display affects the perceived safety of the participants to cross but not all communication possibilities have the same effect. In the study by Clamann et al. (2017) participants were told that they were late for a job interview before the crossing task. They were confronted with a van with a communication display (an LCD screen) in front which could show a pedestrian walking sign, the same sign but crossed through, and information about the vehicles speed profile. The results indicate that the communication display did not influence the crossing behavior of the participants. Thus, no concrete conclusion can be drawn so far on the effect of communication displays on crossing behavior and therefore more research is needed. However, this type of studies is, despite its relatively high degree of realism, costly, time consuming, dependent on weather and traffic conditions, and are strictly ethically examined, which limits their adoption and replication.

Studies that are to a lesser extent affected by such factors are those performed in simulated environments through Virtual Reality (VR). However, VR has also drawbacks, for example: the setting can be unrealistic, the behavior of vehicles can be arbitrary and affect the risk perception due to the feeling that it is unrealistic. Therefore, careful design of these types of experiments is required. Such studies are also scarce in the literature in this specific field. Among the few available VR studies, one study attempted to simulate eye contact by placing 'eyes' on the vehicles' headlamp. The participants were asked to press a button to cross the street safely and at their earliest convenience. The faked eye contact between the car and the participants was found to make them decide faster and more accurately whether to cross or not, while making them feel safer too (Chang et al., 2017). Farooq, Cherchi, and Sobhani (2018) developed a Virtual Immersive Reality Environment (VIRE) to overcome the lack of realism in stated preference experiments. VIRE was used to examine the crossing behavior of pedestrians in front of AVs in different scenarios. The results were compared to the participants' decisions when (1) reading a text-only version of the same crossing scenarios; and (2) with an animated video of the same scenarios. The researchers found that older people and male participants preferred to cross in an unsignalized intersection with an AV as compared to a signalized intersection with a non-AV. The difference in age was small (range = 19–40, M = 26, SD = 5). The results showed that most of the participants preferred to cross in front of the AV in the VIRE. However, in this study the vehicles were presented under different circumstances and therefore no clear conclusion can be drawn. The preference for AVs was not found using the other two methods mentioned above (text-only and animated videos). The authors attribute this effect to the lack of realism of the other methods.

There are several other VR studies performed on pedestrians' crossing behavior, especially children, which have shown that VR can reveal differences in their crossing behavior (Oxley, Ihsen, Fildes, Charlton, & Day, 2005; Shochet, Dadds, Ham, & Montague, 2010; Simpson, Johnston, & Richardson, 2003). In addition, studies have suggested that VR can be highly immersive (Farooq et al., 2018; Feldstein, Dietrich, Milinkovic, & Bengler, 2016) and that behavior in a VR simulation can match real world norms when performed well (Deb, Carruth, Sween, Strawderman, & Garrison, 2017).

As can be seen from the current state-of-the-art, VR studies have the potential to reveal behavioral change and can be used to study interactions between AVs and vulnerable road users. Therefore, the main objective of the present study is to investigate the interactions between pedestrians and AVs using VR simulation of a crossing situation involving an AV by using 360° videos. The advantages of 360° videos are the use of realistic looks from the real world in a controlled setting at a low cost and high reproducibility. We define an interaction as a traffic event involving two or more road users (in this case an AV and a pedestrian), which can affect their behavior and as a result their safety and traffic efficiency. Examples of such interactions are crossing an intersection, switching lanes, and overtaking. We assume that present-day interactions are influenced by visual and auditory communication between road users. Eye contact, for example, is a form of communication which affects these interactions (Guéguen, Eyssartier, & Meineri, 2015). This, however, may not be present when AVs become driverless. In addition, AVs could have many appearances, including displays made for communication purposes, the so-called external Human-Machine Interfaces (eHMIs). These new appearances could impact road users' behavior (Klatt, Chesham, & Lobmaier, 2016). In addition, road users could behave differently when interacting with AVs because they have certain expectations of these vehicles. Expectations influence the decision making and thus the behavior of road users (Houtenbos, Jagtman, Hagenzieker, Wieringa, & Hale, 2005). For example, we expect that when road users interact with AVs for the first time, they will not have clear expectations about the AVs' behavior, and thus could be more cautious. With the introduction of automated vehicles on the road, specific knowledge on how VRUs will behave and how eHMIs affect their behavior is important. It can steer the road and transport (safety) policies in this regard and can help manufacturers in producing safe AVs. We have previously developed a theoretical framework which is helpful to use to increase our understanding of psychological factors influencing the interactions between AVs and road users (Núñez Velasco, Farah, Arem, & Hagenzieker, 2017), as illustrated in Figure 3.

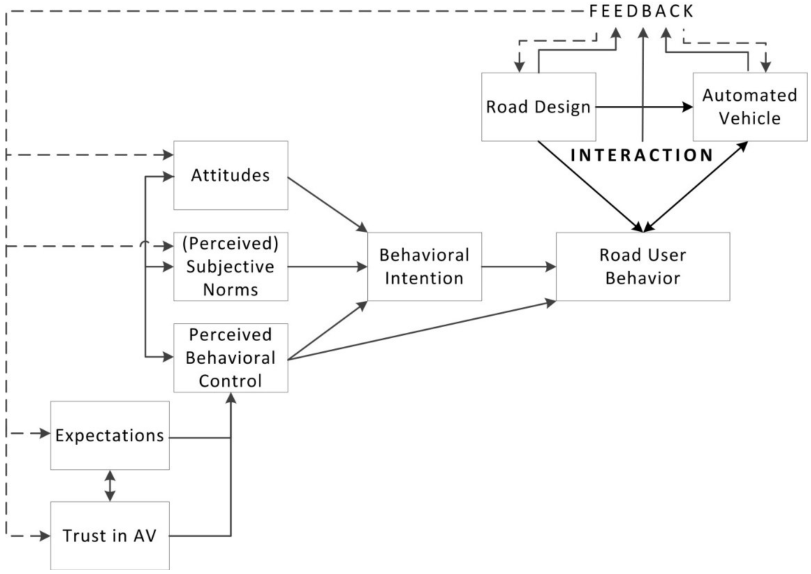

Figure 3. Theoretical framework explaining the way AVs could affect VRUs' behavior (Núñez Velasco et al., 2017).

This framework builds upon the Theory of Planned Behavior, which explains that behavior is influenced by behavioral intention and perceived behavioral control – the control one perceives to have to successfully carry out the behavior. The behavioral intention is influenced by attitudes, subjective norms, and perceived behavioral control (Ajzen, 1991). According to our framework behavior is influenced also by the road design, the automated vehicles' behavior, road users' expectations, their trust level, and behavioral adaptation. Road users' behavior will change over time as they learn and create more accurate and concrete expectations of the AV's behavior, and as they adapt their trust levels. In addition, assisting road users in creating the right expectations could guide them to safer and more efficient behavior, for example by displaying a green light indicating that the pedestrian can cross when the vehicle is decelerating as compared to displaying nothing. So, AVs' characteristics could guide road users' behavior, but research is needed to understand *how* these interactions will be affected.

In this study we investigate the interactions between pedestrians and AVs. We use a VR simulation of a crossing situation involving an AV using 360° videos. The two main aims of the study are: (1) to investigate how the physical appearance of the AV and a mounted eHMI affect pedestrians' crossing intention; and (2) to assess the perceived realism of VR based on 360° videos for research on pedestrian crossing behavior. The movement within the VR environment is not possible because it displays recorded videos, so only participants' intentions were studied. The theoretical constructs considered were perceived behavioral control and trust in automation. The perceived behavioral control is one of the strongest predictor of intentions and behavior and is also able to explain variation in those independently of the attitudes and subjective norms (Armitage & Conner, 2001). The trust in automation was measured to study the relationship with perceived behavioral control. The remainder of the article is structured as follows: Section 2 discusses the research methodology, section 3 presents the results and finally, in section 4 the discussion and conclusions are presented.

3.2 Research Methodology

This study used a repeated measures design where each participant in the experiment experienced several video scenarios displaying different scenes. The scenarios were presented to the participants using consumer-grade VR glasses and a Samsung Galaxy S6 screen. The scenarios differed in the following variables: vehicle type, driving speed, time gap, presence of a crossing facility, and presence of a traffic sign on the vehicle (as presented in Table 1), which resulted in 8 scenarios of the CV (2 x speed, 2 x time gap, and 2 x crossing facility) and 24 scenarios of the AV (2 x speed, 2 x time gap, 2 x crossing facility, and 3 x signs), so in total 32 scenarios. These scenarios were presented in three different randomization to account for order effects. We chose to examine 2 types of vehicles; one resembling a traditional vehicle and the other resembling an AV shuttle. Some AVs have a different appearance compared to contemporary vehicles and it is not clear how this affects pedestrians' behavior. This is also the case for eHMIs on the vehicle. As mentioned before, the research that has been performed so far is inconclusive about these two factors and therefore we have decided to consider them in this study. In addition, the gap between a pedestrian and a vehicle is a typical variable that was considered in previous crossing behavior studies (Rodríguez Palmeiro et al., 2018; Yannis, Papadimitriou, & Theofilatos, 2013) and therefore is as well considered in this study. We choose for a gap of 2 and 4 seconds because the vehicle had to be clearly visible in the videos and therefore a small gap was required. The literature shows that the critical crossing gap lies between 5 and 9 seconds (Brewer, Fitzpatrick, Whitacre, & Lord, 2006), and that there is a negative relationship between critical gaps and driving speeds (Kadali & Vedagiri, 2013). We did not want to have a gap that would be accepted or rejected by everyone. In addition, we have conducted a pilot study to investigate the initial selected gaps which resulted in the gaps used in this study. Another factor that had to be taken into account is the camera resolution. If the vehicle was too far away, the picture quality would be too low to show the vehicle adequately. So, these factors resulted in the chosen gaps. We considered in the study two speeds, 20 km/h and 10 km/h. These speeds of the vehicles were chosen because the maximum speed of the chosen AV shuttle is 20 km/h when manually driven but when it is operated in automated mode its maximum speed was 15 km/h. These speeds also fit the environment in which the recordings took place. The environment is an access road to the university with a maximum allowed speed of 30 km/h. So, the chosen speeds of 20 & 10 km/h fit the combination of the maximum speed of the WEpod in automated mode and the environment. The difference of 10 km/h was added to capture its effect on the crossing intention of the different participants. Finally, the presence of a crossing facility, a relevant factor according to our proposed model (J Pablo Núñez Velasco et al., 2017) and previous studies (Kadali & Vedagiri, 2016; Kadali, Vedagiri, & Rathi, 2015), was considered to examine differences in crossing intentions of pedestrians.

3.2.1 Sample description

In total, 55 individuals participated, of which 32 were male (58%) and 23 were female (42%). The sample size was based on previously performed studies that had a similar set up as our own study (Clamann et al., 2017b; Rodríguez Palmeiro et al., 2018; Rothenbücher et al., 2016). The age of the participants ranged between 21 – 37 with an average of 24.9 years old and standard deviation of 3.5 years. The interested individuals were asked to sign a consent form prior to their participation in the experiment. The participants were mostly recruited at Delft University of Technology, in the Netherlands. An advertisement about the experiment was announced through social media, and printed posters at different locations at the university campus. In the advertisement we provided information regarding the total duration of the experiment (50 minutes) and that it focuses on pedestrian crossing behavior in virtual reality (VR), but without mentioning automated vehicles. The participants were compensated for their time with a voucher of €15 at the end of the experiment.

Table 1. Variables included in this experiment.

Variable name	Levels	Annotation	Explanation
Vehicle type (figure 4)	2	AV	Automated Vehicle
		CV	Conventional Vehicle
Crossing facility	2	Z	Zebra Crossing present
		NZ	No Zebra Crossing present
Vehicle speed	2	V1	Vehicle driving speed 10 km/h
		V2	Vehicle driving speed 20 km/h
Gap size	2	Gap2s (G2s)	Gap between vehicle and pedestrian was 2 seconds
		Gap4s (G4s)	Gap between vehicle and pedestrian was 4 seconds
eHMI* (see figure 5)	2	Green sign (G)	The AV was equipped with a green sign on the front window
		Red sign (R)	The AV was equipped with a red sign on the front window

Note: * eHMI was only shown on the AV.

3.2.2 VR Experiment

The videos were recorded on a two-way street that is 8 meters wide at the Delft University of Technology campus on a cloudy day. This location was relatively quiet, easily accessible and contained an intersection, which is why it was chosen and was approved by the Ethical committee of Delft University of Technology. The road was closed off when we were filming, and therefore no other vehicles were visible in the recordings. We used a Nikon Keymission 360 mounted on a tripod at a height of 1.75 meters with a resolution of 3480x2160 and 24 frames per second. These videos were then presented to the participants using a consumer level head-mounted display. The device that was used was a Samsung Galaxy S6 using the VR Media Player app found on the Play store. This device has an AMOLED 5.1-inch screen with a resolution of 1440 x 2560.

The scenarios were made using 8 different video recordings: 2 recordings of the camera approaching the intersection with a speed of approximately 1.4 m/s to simulate the walking speed, one scenario with and one without the zebra crossing, 2 recordings per type of vehicle (automated or manual), one at a driving speed of 10 km/h and one at a driving speed of 20 km/h. For this experiment, we used 2 vehicles (Figure 4): a Volvo V40 from 2001 to represent a conventional vehicle (CV) and an Easymile EZ10 operated by a steward to represent an automated vehicle (AV).

Figure 4. Left the automated vehicle (WEpod Welly) is shown as it was seen in the video's recordings. On the right the conventional vehicle is shown (Volvo V40).

We alternated the presence of a zebra crossing. The videos were then cut into pieces to create the gaps by ending the video 2 or 4 seconds before the vehicles reached the location of the zebra crossing. The signs were mounted only on the automated vehicle using Adobe Premiere Pro as can be seen in figure 5.

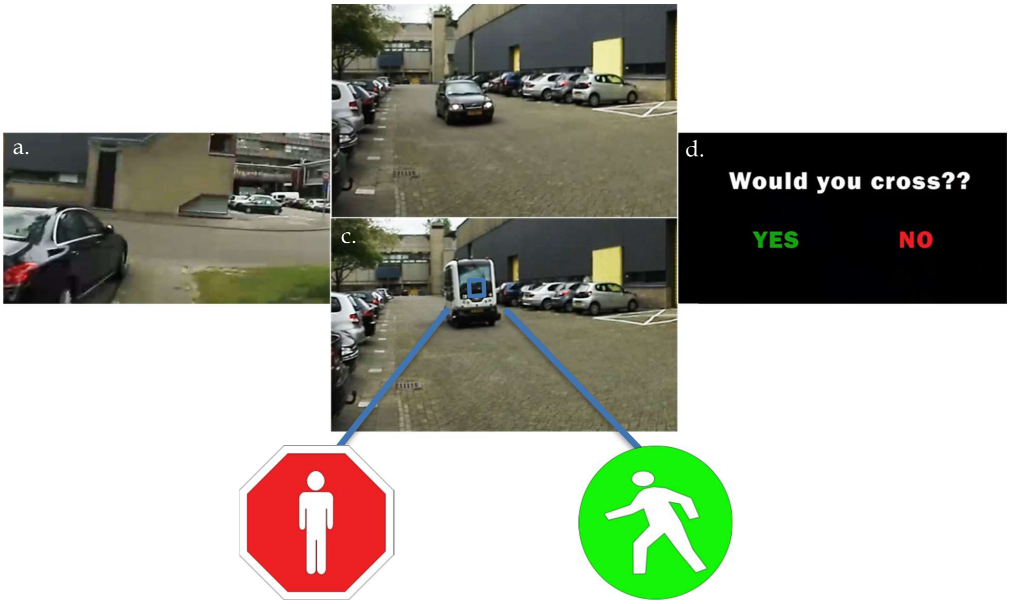

Figure 5. Illustration of how a VR trial could look like. From left to right, it started with scene 'a' in which the participant appeared to walk towards the intersection. Scene b & c present two examples of the 32 scenarios. In this case scene 'b' shows the CV and 'c' the AV. Scene d prompted the pedestrians whether they would cross or not. At the bottom of the figure, the displays are shown that were added on the AV using video editing software.

3.2.3 Surveys

In this we asked the participants to complete several surveys as following:

Pedestrian Behavior Scale (PBS)

The 23-item version of the Pedestrian Behavior Scale (PBS) (Granié, Pannetier, & Guého, 2013) was used in order to identify and categorize the behavior of the participants as pedestrians. This questionnaire consists of four factors: transgression, lapses, aggressive behavior, and positive behavior. PBS consists of items such as: *I cross diagonally to save time*, *I cross the street between parked cars*, *I cross without looking because I am talking to someone*, and *I get angry with another user and insult him.* Participants reported on a scale from 1 (never) to 7 (often) how often they performed certain behavior.

Trust in Automation
In order to measure trust in automation, we have used an adapted version of the trust questionnaire developed by Payre, Cestac and Delhomme (2016). It contains 6-items which had to be answered on a scale from 1 (Strongly disagree) to 7 (strongly agree), such as: *Globally, I trust the automated vehicle*, and *I trust the automated vehicle to avoid obstacles*. The internal consistency of the original questionnaire was found to be acceptable according to the authors ($\alpha = .82$).

Perceived Behavioral Control
We measured Perceived Behavioral Control after each trial in the first VR session and used the mean of two items that were scored on a 7-point bipolar scale. The items used were: '*For me, crossing the road in this way would be...'*, and '*I believe that I have the ability to cross the road in this way...'* adopted from Zhou, Horrey, and Yu (2009). The first item was scored from very easy (score 1) to very difficult (score 7), and the second from strongly agree (score 1) to strongly disagree (score 7). In addition, the perceived risk was assessed with the item '*Crossing the road in this situation would be...'* and was scored from very unsafe (score 1) to very safe (score 7) on a 7-point scale (Zhou et al., 2009a).

Presence Questionnaire
At the end of the experiment, a 19-item version of the Presence Questionnaire (version 3.0) was used to test the immersiveness of the virtual environment (Singer & Witmer, 1999; Witmer & Singer, 1998). The 19 items that were chosen, are the marker variables of the presence questionnaire 4-factor model (1-8, 14, 19, 21-25, 30, 31). Finally, we discarded the 2 items (11, 12) about sound quality and localization as there was no sound presented. The items included questions such as: '*How much did your experiences in the virtual environment seem consistent with your real-world experiences?'*, and *'How much did the visual display quality interfere or distract you from performing assigned tasks or required activities?'* We omitted questions about haptic fidelity as this was not applicable to our experiment.

Misery Scale (MISC)
In between sessions, we used the Misery Scale (MISC) to keep track of the participants well-being over time and severity (Van Emmerik, De Vries, & Bos, 2011). The scale measures motion sickness on a scale from 0 (no problems) to 10 (vomiting). We stopped the experiment if participants reached a score of 4 (medium dizziness, headache, stomach awareness, and or sweating, etc.) or higher as requested by the TU Delft ethical committee. The response rate for all the surveys was 100%.

3.2.4 Procedure

After being informed about the experimental procedure the participants were asked to sign an informed consent. Due to the nature of the experiment extra attention was put on informing the participants about possible symptoms to help them to be aware what they could experience (such as: stomach awareness and nausea). Afterwards, the participants were asked to fill in a survey about their demographics (age, gender, nationality, etc.) and to fill in the PBS. Following this, the VR experiment started in which they had to wear the head-mounted display (HMD). The participants experienced 32 short virtual environment scenarios in the form of a 360° video. During each scenario a pre-recorded 360° video was shown through the HMD containing a part where the participant approaches the intersection, followed by one of the 32 scenarios. The duration of each scenario was 3 seconds. At the end of each scenario the following question appeared in the HMD; *'Would you cross?'* (see Figure 5). The participants had to react quickly and verbally once they saw this question. Then, the next trial started. The videos were divided in 3 sessions of 11, 11, and 10 videos, with a break of 1 minute minimum in between sessions. In the first session we asked the participants to answer 3 questions about their perceived behavioral control following the question *'Would you cross?'*. To make sure that the participants were feeling well, the Misery Scale (MISC) was completed by the participants before starting the experiment and after each of the first two sessions. At the end of the experiment, the participants were prompted to fill in the Presence Questionnaire. Afterwards, we asked the participants whether they had experienced VR before and how that experience had been. Finally, the participants completed the trust in AVs questionnaire. In total, the experiment took 45 minutes per participant.

3.3 Results

In this section we first present descriptive statistics (3.1), including the characteristics of the participants (such as: age, gender, prior knowledge of automated vehicles), followed by the results of a mixed model analysis that accounts for the potential affecting variables simultaneously (3.2), and for the repeated measures for each participant. In section 3.3 the results of Perceived Behavioral Control are presented. The realism assessment is presented in section 3.4 and includes the results of both the Misery Scale (MISC) and the Presence Questionnaire.

3.3.1 Descriptive Statistics

Fifty-five individuals participated in our experiment. The age of the participants ranged between 21 and 37 (*M* = 25.0; *SD* = 3.5). There was no significant difference in age between males (*M* = 25.4; *SD* = 3.9) and females (*M* = 24.4; *SD* = 2.8), *t* (23) = 1.023, *p* = .311. 37 of the participants were students and 15 were employed full time at Delft University of Technology. The remaining 3 were unemployed. In terms of highest degree of education obtained, 2 of the participants had a high school degree, 34 had a bachelor's degree, 16 master's degree, and 2 doctorate degree. Two participants failed to complete the experiment due to simulation sickness.

Out of the 55 participants, 53 stated to know in general what an automated vehicle is. Overall, they defined an automated vehicle as a vehicle that takes over tasks of human drivers to a certain extent. Further, 32 participants (20 males; 12 females) knew that the AV used in our study (the WEPod) was an automated vehicle. There was no significant difference in gender in terms of the identification of the type of vehicle (i.e. if it was automated or manual), χ^2 (1) = 0.586, *p* = .444.

The overall trust in automation mean was 4.81 (*SD* = 1.08) on a 7-point Likert scale (with score 7 meaning strongly agree). There was no significant difference between males (*M* = 5.1, *SD* = 1.1) and females (*M* = 4.5, *SD* = 1.0) with respect to their trust levels in automated vehicles, *t* (53) = 1.957; *p* = .056. There was a statistically significant difference in trust between participants who identified that the automated vehicle was an automated vehicle (*M* = 5.1, *SD* = 1.0) and those who did not identify it as such (*M* = 4.3, *SD* = 1.0), *t* (53) = 2.907; *p* = .005.

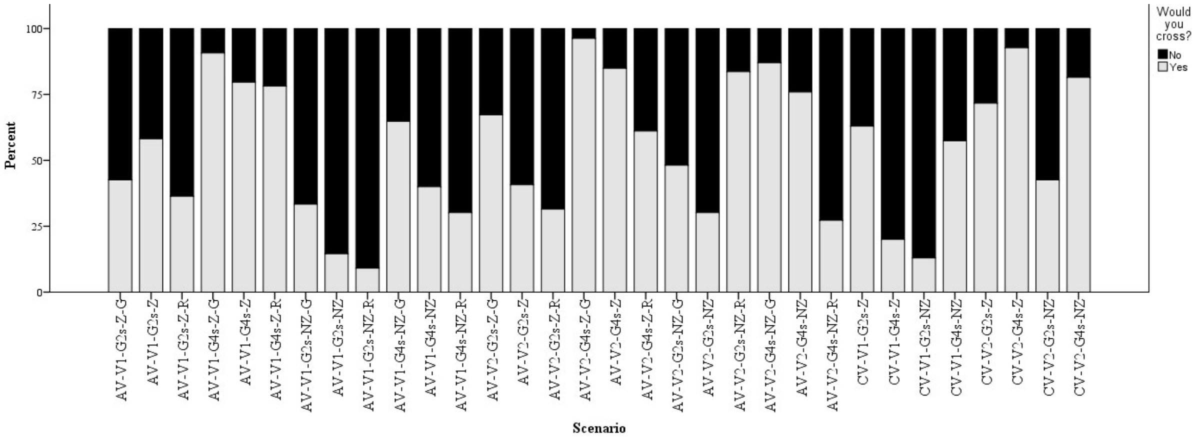

Figure 6. Bar graph displaying the crossing intentions percentage per scenario. The annotation list can be found in Table 1.

Participants who identified that the WEpod was automated showed higher levels of trust in automated vehicles.

3.3.2 Pedestrians crossing intentions

Crossing intentions were scored 0 if the participant decided not to cross and 1 if he/she decided to cross. In 54.8% (n=951) of all trials (N_{All} = 1735) participants intended to cross. In trials with conventional vehicles (N_{CV} =433) the percentage of participants intending to cross was 55.2% compared to 54.6% for automated vehicles without signs (N_{AVns} =433). In addition, in scenarios containing AVs with signs (N_{AVws} = 869) the percentage of participants who intended to cross was 55.5%. When comparing between gender, females intended to cross in 59.4% of the trials (n = 422) and males in only 51.6% of the trials (n = 528). Participants who did know that the automated vehicle was an automated vehicle intended to cross in 51.9% of the trials (n = 518), while those who did not know intended to cross in 58.7% (n = 432) of the trials.

To investigate the significance of these differences we have estimated a binomial logistic regression model with mixed effects which accounts for the vehicle type, speed of the vehicle, presence of a zebra crossing, and the gap size between the vehicle and the pedestrian on the intentions to cross or not (a dichotomous variable). The odds ratios (OR) are displayed to show the effect sizes. A random intercept was added to capture individual differences. Furthermore, an unstructured covariance matrix was assumed because of a lack of assumptions in the error structure (Singer, 1998). Two separate models were developed and estimated to account for the correlation between gap size measured in time and in distance (e.g. Oxley et al., 2005). The time gap is a function of distance and speed and thus we remove speed from the equation if we use the gap as the distance in meters between the pedestrian and the vehicle. The models were estimated first while accounting for the type of the vehicle, vehicle speed, zebra crossing and gap size only (I). Then, the participants' characteristics were added, as well as the communication signs that were placed on the vehicle (II). The results of models I are presented in Tables 2a and 3a, while the results of models II are presented in Tables 2b and 3b. The extended models did not perform better than the simpler ones but are mentioned here because these additional variables had been examined in previous studies and are therefore of interest. We have also tested the interaction effects, but none were significant and are therefore not reported.

Table 2a. Estimation results of the crossing intention model (I).

Fixed Coefficients		Estimate(SE)	Odds Ratio	95% CI	p
β_0	Intercept (mean)	0.89(0.19)	2.43	[1.66,3.57]	<.001
$\beta_{Vehicle\ Type}$	Vehicle type (AV, CV*)	-0.02(0.13)	0.98	[0.76,1.26]	.86
β_{speed}	Speed (10, 20* km/h)	-0.94(0.11)	0.39	[0.31,0.49]	<.001
β_{Zebra}	Zebra crossing present (yes, no*)	0.89(0.11)	2.44	[1.96,3.04]	<.001
$\beta_{Gapsize}$	Gap size (seconds; 2 s, 4* s)	-1.21(0.11)	0.30	[0.24,0.37]	<.001
Random Effects			Estimate(SE)	Z	p
μ_0	ParticipantID: intercept (var)		0.92(0.23)	4.07	<.001
Model Performance					
-2LL	7923.8				
AIC	7925.3				
BIC	7930.7				

*Reference category.

Table 2b. Estimation results of the crossing intention model (II).

Fixed Coefficients		Estimate(SE)	Odds Ratio	95% CI	p
β_0	Intercept (mean)	0.01(0.67)	1.01	[0.27,3.75]	.99
$\beta_{Vehicle\ Type}$	Vehicle type (AV, CV*)	-0.11(0.16)	0.90	[0.66,1.22]	.49
β_{speed}	Speed (10, 20* km/h)	-0.98(0.11)	0.29	[0.23,0.36]	<.001
β_{Zebra}	Zebra crossing present (yes, no*)	0.93(0.11)	0.38	[0.30,0.47]	<.001
$\beta_{Gapsize}$	Gap size (2 s, 4 s*)	-1.26(0.12)	2.53	[2.02,3.17]	<.001
$\beta_{GreenSign}$	Sign mounted (green sign, no sign*)	0.73(0.16)	2.08	[1.51,2.85]	<.001
$\beta_{RedSign}$	Sign mounted (red sign, no sign*)	-0.44(0.16)	0.65	[0.47,0.88]	.01
β_{Trust}	Trust in AVs	0.33(0.14)	1.30	[0.99,1.73]	.02
$\beta_{Recognized}$	Recognized WEpod (yes, no*)	-0.31(0.31)	0.53	[0.29,0.98]	.04
Random Effects			Estimate(SE)	Z	p
μ_0	ParticipantID: intercept (var)		0.88(0.23)	3.905	<.001
Model Performance					
-2LL	7998.6				
AIC	8000.6				
BIC	8006.1				

*Reference category.

All variables except type of vehicle had a significant effect on the crossing intentions of the participants, as can be seen in Table 2a. Presence of a zebra crossing and gap size between the pedestrian and the vehicle showed direction of impact as would have been expected: Crossing intention was higher with zebra crossing and with bigger gap size. In contrast to our expectations, participants intended to cross less often when the speed of the vehicle was lower. Replacing the gap size measured in seconds by the one measured in meters results in an insignificant effect of speed (Table 3a and Table 3b). Also, gap size (in meters) had the strongest effect on crossing intention, meaning that the distance is the most important factor affecting crossing intentions. Additionally, we tested the effect of trust in automated vehicles, gender, and the fact that some participants knew what a WEpod is. Only trust affected the crossing intention positively and had a small effect size (Table 2b). Table 2b and Table 3b also show that recognizing the WEpod as an AV affected the crossing intentions negatively. The effect size was medium. This could be a proxy variable of vehicle type because only the people that were aware of the WEpod being an AV understood that there were two vehicle types, automated and non-automated. In all the models, the random intercept was significant confirming our hypothesis that the repeated observations of participant are correlated.

Table 3a. Estimation results of the crossing intention model with conventional factors and distance gap.

Fixed Coefficients		Estimate(SE)	Odds Ratio	95% CI	*p*
β_0	Intercept (mean)	0.91(0.21)	2.94	[1.66,3.74]	<.001
$\beta_{\text{Vehicle Type}}$	Vehicle type (AV, CV*)	-0.02(0.13)	0.98	[0.76,1.26]	.87
β_{speed}	Speed (10, 20* km/h)	0.27(0.15)	1.31	[0.97,1.75]	.08
β_{Zebra}	Zebra crossing present (yes, no*)	0.89(0.11)	2.44	[1.96,3.04]	<.001
β_{Gapsize}	Gap size (meters; 5.6 m, 22.2* m)	-2.42(0.23)	0.09	[0.06,0.14]	<.001
β_{Gapsize}	Gap size (meters; 11.1 m, 22.2* m)	-1.25(0.16)	0.29	[0.21,0.39]	<.001
Random Effects			Estimate(SE)	*Z*	*p*
μ_0	ParticipantID: intercept (var)		0.93(0.23)	3.99	<.001
Model Performance					
-2LL	7925.3				
AIC	7927.3				
BIC	7932.8				

*Reference category.

Table 3b. Estimation results of the crossing intention model with all factors and distance gap.

Fixed Coefficients		Estimate(SE)	Odds Ratio	95% CI	*p*
β_0	Intercept (mean)	0.04(0.67)	1.04	[0.28,3.88]	.96
$\beta_{Vehicle\ Type}$	Vehicle type (AV, CV*)	-0.11(0.16)	0.90	[0.66,1.22]	.49
β_{speed}	Speed (10, 20 km/h*)	0.28(0.15)	1.32	[0.98,1.78]	.07
β_{Zebra}	Zebra crossing present (yes, no*)	0.93(0.11)	2.53	[2.02,3.17]	<.001
β_{Gapsize}	Gap size (5.6 m, 22.2* m)	-2.52(0.23)	0.08	[0.05,0.13]	<.001
β_{Gapsize}	Gap size (11.1 m, 22.2* m)	-1.30(0.17)	0.27	[0.20,0.38]	<.001
$\beta_{GreenSign}$	Sign mounted (green sign, no sign*)	0.73(0.16)	2.08	[1.51,2.85]	<.001
$\beta_{RedSign}$	Sign mounted (red sign, no sign*)	-0.44(0.16)	0.65	[0.47,0.88]	.01
β_{Trust}	Trust in AVs	0.27(0.14)	1.30	[0.99,1.73]	.06
$\beta_{Recognized}$	Recognized WEpod (yes, no*)	-0.64(0.31)	0.53	[0.29,0.98]	.04
Random Effects			Estimate(SE)	*Z*	*p*
μ_0	ParticipantID: intercept (var)		0.93(0.23)	3.986	<.001
Model Performance					
-2LL	8000.2				
AIC	8002.2				
BIC	8007.6				

*Reference category.

Table 4a. Estimation results of the crossing intention model with all factors, distance gap measured in meters, and PBC.

Fixed Coefficients		Estimate(SE)	Odds Ratio	95% CI	p
β_0	Intercept (mean)	5.79(1.11)	327.13	[36.80,2907]	<.001
$\beta_{Vehicle\ Type}$	Vehicle type (AV, CV*)	-0.10(0.44)	0.90	[0.38,2.14]	.82
β_{speed}	Speed (10, 20 km/h*)	-0.03(0.42)	0.97	[0.43,2.19]	.93
β_{Zebra}	Zebra crossing present (yes, no*)	-0.40(0.32)	0.96	[0.52,1.79]	.90
β_{Gapsize}	Gap size (5.6 m, 22.2* m)	-1.24(0.62)	0.29	[0.09,0.99]	.05
β_{Gapsize}	Gap size (11.1 m, 22.2* m)	-0.41(0.46)	0.66	[0.27,1.64]	.37
$\beta_{GreenSign}$	Sign mounted (green sign, no sign*)	0.45(0.44)	1.57	[0.66,3.76]	.31
$\beta_{RedSign}$	Sign mounted (red sign, no sign*)	-0.50(0.42)	0.61	[0.27,1.39]	.24
β_{Trust}	Trust in AVs	0.54(0.21)	1.71	[1.14,2.56]	.01
$\beta_{Recognized}$	Recognized WEpod (yes, no*)	-0.13(0.43)	0.88	[0.38,2.03]	.76
β_{PBC}	PBC	-2.18(0.19)	0.11	[0.08,0.16]	<.001
Random Effects			Estimate(SE)	Z	p
μ_0	ParticipantID: intercept (var)		0.74(0.37)	1.99	.05
Model Performance					
-2LL	3476.1				
AIC	3478.1				
BIC	3482.5				

*Reference category.

3.3.3 Perceived Behavioral Control (PBC)

PBC was measured during the first VR session (i.e. during the first 11 scenarios) right after asking the participants whether they would cross or not on a 3-item inverted 7-point scale ranging from 1 to 7. 53 participants with their reported PBC after each of the 11 scenarios resulted in 583 PBC measurements. A high negative correlation was found between the crossing intention and PBC, $r = -.737$, $p < 0.001$. This means that the intention to cross correlates with high PBC (notice that we used the inverted 7-point scale). PBC scores were averaged per participant for the sake of comparison. No statistically significant difference was found between males ($M = 3.33$, $SD = 0.89$) and females ($M = 3.00$, $SD = 0.81$), $t(53) = 1.423$, $p = .160$, nor between participants who recognized the WEpod as an AV ($M = 3.35$, $SD = 0.86$) and the ones who did not ($M = 2.98$, $SD = 0.84$), $t(53) = 1.590$, $p = .118$. In addition, no significant difference was found between the PBC participants experienced when confronted with an AV ($M = 3.16$, $SD = 1.63$) as compared to a CV ($M = 3.28$, $SD = 1.77$), $t(585) = -0.736$, $p = 0.462$. When PBC is added to the model of crossing intentions, one finds that PBC is the strongest factor as can be seen in Table 4a. The PBC score had a very strong negative effect (OR = 0.11) on crossing intentions, meaning that a high PBC predicts a high intention to cross. The effect size of PBC was larger than the effect size of gap size on crossing intentions. However, the gap size retains its large effect size but only at the smallest distance (i.e. 5.6 meters).

3.3.4 Miscery Scale (MISC)

The MISC scale was filled in 4 times by the participants, before starting the VR experiment and after each of the three VR sessions. Almost half of the participants (N = 29) had prior experience with a VR environment. Figure 7 visualizes the results. The baseline score was *M* = 0.15, *SD* = 0.52, with a minimum value of 0 and a maximum of 3. After the first VR session the score was *M* = 0.64, (*SD* = 0.87, range 0 to 3), after the 2nd VR session *M* = 0.75 (*SD* = 1.36, range 0 to 6), and after the final VR session *M* = 0.51(*SD* = 0.78, range 0 to 3). In total, 2 participants had to stop the experiment because of scoring higher than a 4 on the MISC. This happened both times after the 2nd session in the VR environment.

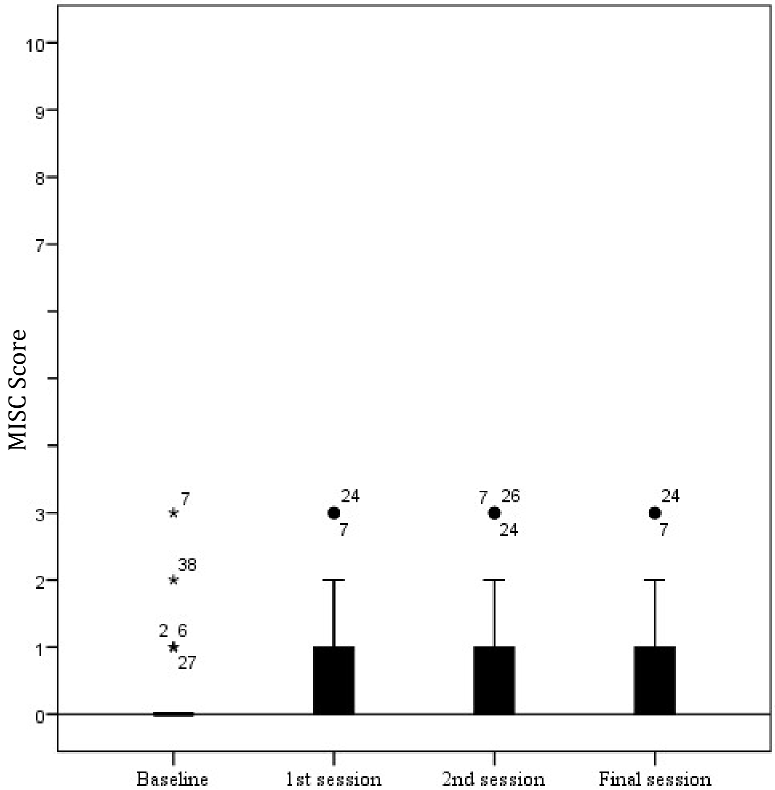

Figure 7. Boxplot representing the MISC results before and after each VR session. On the y-axis the MISC score is plotted. The numbers represent the participant's number.

3.3.5 Presence Questionnaire

Descriptive statistics of the Presence questionnaire data of 19 items on a 7-point scale (from low to high) are shown in Table 4b for the 4 factors: involvement, sensory fidelity, adaptation/immersion, and interface quality (see 2.1.2). The mean score of 4.59 indicates that participants experienced a moderate amount of presence using the HMD. The interface quality received the lowest score and adaptation/immersion the highest.

Table 4b. Descriptive Statistics of the Presence Scales (Range: 1 (low) to 7 (high)).

	Involvement	Sensory fidelity	Adaptation/ Immersion	Interface quality	Total mean
Mean	4.73	5.05	5.26	2.67	4.59
Std. Deviation	0.82	1.10	0.71	1.20	0.53

3.4 Discussion

This research aimed at providing insights into the crossing intentions of pedestrians when interacting with an automated vehicle (AV) as compared to when interacting with a conventional vehicle. In addition, the perceived realism of Virtual reality based on 360° videos for pedestrian crossing behavior for research purposes was assessed. The effects of a different physical appearance and the presence of communication capabilities were studied. Also, speed of the vehicles, the gap between the pedestrian and vehicle, and the presence of a zebra crossing were included as factors that could affect the crossing intention. This resulted in 32 scenarios which were presented to 55 individuals by using smartphone based virtual reality, created with 360 degrees videos.

The main findings were the following. The most significant predictors found of road crossing intentions were speed of the vehicle, gap size between the pedestrian and the vehicle, and the presence of a zebra crossing. The gap size (in meters) was the strongest factor in almost all of the models. This is congruent with the literature (e.g. Oxley et al., 2005) and was expected. Contrary to expectations, no difference was found in crossing intention between vehicle types. However, this result is in accordance with some literature (Clamann et al., 2017b; A. Rodríguez Palmeiro et al., 2018; Rothenbücher et al., 2016). According to some, this has to do with the pedestrians not deviating from their established crossing strategy (Clamann et al., 2017b) or due to their high amount of experience with interacting with other vehicles (Rothenbücher et al., 2016). However, participants that were aware of the vehicle being an AV intended to cross less. This could be coming from a distrust of vehicles as they are now but trusting the vehicles as how they could be as mentioned by others. One explanation is that these participants might be knowledgeable of the limitations that current AVs have and therefore were more careful. So, the scale used to capture their trust could be measuring their trust in future AVs instead of the ones already operating. It could be that once the participants are asked to fill it in according to their trust in the vehicle, they saw that their trust scores would match their crossing intentions. The fact that the participants may have answered the Trust questionnaire with a future version of AVs in mind, could mean that the trust values are not relevant when it comes to the interactions with the used AV. However, it remains unclear whether that was the case. Future work could shed light on this matter. Furthermore, a new questionnaire is now available specifically targeting the receptivity of pedestrians toward AVs (Deb, Strawderman, et al., 2017). Future research could compare the performance of both questionnaires.

Although the vehicles differed in size and this could have influenced the participants' crossing intentions (Delucia, 2013) we did not find this effect to be statistically significant in this study. There was no significant interaction effect found between the variable 'vehicle type' and 'Recognized AV' which means that the participants did not have different crossing intentions based on the vehicle type whether they recognized it as an AV or not. If vehicle size had an effect, we would at least expect it to affect the crossing intentions of the participants who did not recognize the WEpod as an AV, meaning that vehicle size alone has not affected the crossing intentions. Therefore, we conclude that vehicle size did not affect the crossing intentions in this study. The speed of the vehicle showed a counter intuitive result in all but the models including gap size as a distance instead of a measurement of time. Participants crossed more often when the speed was 20 km/h as compared to 10 km/h. This is probably related to the fact that we used a time-based gap size. In other words, when a vehicle drove 20 km/h it started further away from the pedestrian and ended further away than when the vehicle drove 10 km/h. When the gap size measured in meters was included in the models, the direction of impact of speed turned out as expected, as was the case in Oxley, et al. (2005). In addition, the gap size measured in distance and in time between pedestrian and vehicle showed expected results in the estimated models. When the gap size was 4 seconds as compared to 2 seconds participants tended to cross more. Overall, gap size measured in meters was a stronger predictor than gap size measured in seconds.

Almost all of the participants had knowledge of automated vehicles in general prior to the participation in our experiment. Of all the participants, 58% of them recognized the WEpod in the experiment and thus knew that it was automated vehicle. In general, participants had average trust in automated vehicles. This result was surprising since most of the participants were students of the Delft University of Technology and had knowledge about AVs, and therefore it was expected that they would have more than average trust in automated vehicles. One could expect that knowledge, or familiarity, leads to trust and thus that our participants would have more than average trust in AVs. Indeed, those who knew that the vehicle was automated had more trust in automated vehicles than those who did not. In another study, those who knew about the used AVs had similar levels of trust as the ones who had experienced driving a simulated AV (Gold, Körber, Hohenberger, Lechner, & Bengler, 2015). They could also have more knowledge about the potential of AVs in general, which could then lead to higher trust levels. It could also lead to a higher perceived safety and thus more trust compared to the ones unaware of the potential of such vehicles. There was no difference in trust levels in automated vehicles between male and female participants. Also, gender did not appear to be a statistically significant predictor of crossing intentions. No difference were found in crossing intentions between genders at all (Male $M = 5.1$ and $SD = 1.1$, Female $M = 4.5$ and $SD = 1.0$); $t(53) = 2.0$, $p = 0.06$. This is in disagreement with previous studies on crossing intentions (e.g. (Holland & Hill, 2007)). Finally, the signs displayed on top of the WEpod showed results in line with our expectations. Participants had more crossing intentions when they were confronted with a green sign, as compared to no sign. And, participants had less crossing intentions when confronted with a red sign, as compared to no sign. Meaning that these types of eHMIs can affect the road users' intentions. The intentions agreed with the eHMIs' intended meaning. Thus, the eHMIs were clear for the participants.

Trust in AVs showed that participants who have more trust, have more intent to crossing. This could be explained by the participants heightened perceived safety due to their trust in AVs. Therefore, they decide to cross more. Participants that were familiar with the AV had higher trust levels than those who were not. Perceived behavioral control was measured using a 3-item inverted 7-point scale. A high, positive, and significant correlation between PBC and intentions to cross were found, meaning that participants with high PBC had higher intentions to cross. In addition, PBC proved to be a strong and good predictor of crossing intentions, with a larger effect size than speed and gap size. However, we only recorded the data of the first 11 scenarios because it would have made the experiment too long (1 session of 11 videos was 10 minutes instead of 3) and it made the task (too) repetitive according to our participants in a pilot study. This reduced the amount of data we could use for the model. The PBC questions were asked after the questions "Would you cross". So, the participants reported their intentions before they answered the PBC questions. This is reversed as compared to what the TPB model suggest. We choose this because it enables the participants to respond quicker whether they would cross or not, which was our main measure used in this study. If we had asked the PBC questions first, we would have given the participants more time to think about their answers making, which could have made them second guess their decision. Further, no difference was found between the participants in terms of PBC regarding their age and gender. The high correlation was a finding we expected according to the Theory of Planned Behavior (Ajzen, 1985). No difference was found in PBC when participants faced an AV as compared to a CV. So, the difference in PBC was not enough to trigger different intentions for crossing. This was surprising because despite that a difference was found in trust in automation, it proved not to be enough to change the crossing intentions. Another possibility would be that the relationship assumed in our theoretical framework (Núñez Velasco et al., 2017) does not exist.

A second aim was to explore how this smartphone and 360 degrees videos-based VR method performed as a research tool. Therefore, we examined the results of the MIsery SCale (MISC), and the results of the presence questionnaire. 2 out of 55 participants had to stop the experiment due to simulation sickness. Overall, most participants reported no symptoms during the whole experiment. The mean did not exceed .75 out of 0 – 10. Although VR experiments using HMD are known for inducing cybersickness the most (Rebenitsch & Owen, 2016), only 2 participants experienced these symptoms in our experiment. This means that the inducement of cybersickness by our VR method was lower than experienced in previous studies. The presence questionnaire was used in this experiment to measure the amount of immersion. The scale ranged from 1 to 7. The higher the score, the more immersive the experience was. Here, the participants gave this VR method a mean score of 4.6. The lowest rating was given to the interface quality. Further, the findings acquired with this research tool are in accordance with the literature despite of the difference in research methods. The fact that the participants did not experience any consequences based on their crossing intentions could be a limitation of virtual reality-based studies. This could have made it possible for the participants to make unsafe decisions which would not be found in real life crossing situations. However, Bhagavathula, Williams, Owens, and Gibbons (2018) revealed in a similar study where pedestrians' crossing behavior in virtual environments was compared with their behavior in a real life experiment that the decisions made in real life and in virtual reality are similar. This is an indication of the validity of this method but future research comparing this smartphone and 360 degrees videos-based VR method with other kinds of VR methods and field studies could assess its performance more clearly. We conclude that this VR method is immersive enough and does not induce simulation sickness to the majority making it a useful research tool.

3.5 Conclusions

The crossing intentions of pedestrians do not differ depending on whether they cross in front of an AV or a CV. Knowledge and familiarity with automated vehicles are correlated with higher trust in automation levels. Perceived behavioral control has a strong relationship with crossing intentions and does not differ depending on vehicle type. Finally, smartphone and 360 degrees videos-based VR method was a useful research methodology.

Chapter 4 – Cyclists' Crossing Intentions when Interacting with Automated Vehicles: A Virtual Reality Study[3]

Abstract

Most of cyclists' fatalities originate from collisions with motorized vehicles. It is expected that Automated Vehicles (AV) will be safer than human driven vehicles, but this depends on the nature of interactions between non-automated road users, among them cyclists. Little research on the interactions between cyclists and AVs exists. This study aims to determine the main factors influencing cyclists' crossing intentions when interacting with an automated vehicle as compared to a conventional vehicle (CV) using a 360° video-based Virtual Reality (VR) method. The considered factors in this study included vehicle type, gap size between cyclist and vehicle, vehicle speed, and right of way. Each factor had two levels. andIn addition, cyclist's self-reported behavior and trust in automated vehicles were also measured. Forty-seven participants experienced several16 different crossing scenarios in a repeated measuresVR study using VR. These scenarios are the result of combinations of the studied factors at different levels participants were confronted with the difference in vehicles and the scenarios were repeated. In total, the experiment lasted 60 minutes. The results show that the gap size and the right of way were the primary factors affecting the crossing intentions of the individuals. The vehicle type and vehicle speed did not have a significant effect on the crossing intentions. Finally, the 360° video-based VR method scored relatively high as a research method and comparable with the results of a previous study investigating pedestrians' crossing intentions confirming its suitability as a research methodology to study cyclists' crossing intentions.

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[3] This chapter was first published: Núñez Velasco, J. P., de Vries, A., Farah, H., van Arem, B., & Hagenzieker, M. (2021). Cyclists' Crossing Intentions When Interacting with Automated Vehicles: A Virtual Reality Study. Information, 12(1); 7

4.1 Introduction

The majority of cyclists' fatalities originate from collisions with motorized vehicles in the Netherlands (SWOV, 2017). As the share of cyclists is increasing, and not only in the Netherlands (Pucher & Buehler, 2017), it is of importance to understand how they behave and will behave when interacting with new types of motorized vehicles, such as automated vehicles. The effects of automated vehicles (AVs), possibly with a new driving style, might lead other road users to change or adapt their behavior. To successfully implement AVs in urban settings, AVs need to be able to understand the intent of cyclists. Therefore, computer algorithms are being developed that can predict intention of cyclists based on hand signaling (Saleh et al., 2019). AVs need to detect and recognize other road users, automated or non-automated, to interact safely with them. Multiple studies have been performed from the point of view of AVs regarding their ability to recognize other road users (Keller & Gavrila, 2014; Li et al., 2017; Schmidt & Färber, 2009). Also, smart infrastructure is proposed to create a safer environment in which cyclists can interact with AVs. The AVs could send information to an upcoming intersection and the intersection could then adapt to create an environment that fits the upcoming interaction (Grembek, Kurzhanskiy, Medury, Varaiya, & Yu, 2019). However, there is less emphasis on how these AVs will interact and communicate with other road users, such as manually driven cars, pedestrians and cyclists (Hagenzieker et al., 2020; Merat, Louw, Madigan, Wilbrink, & Schieben, 2018), and how these other road users will interact with AVs. Non-automated road users need to adapt to a changing road traffic system and to a new type of vehicles (Vissers, Van der Kint, Van Schagen, & Hagenzieker, 2016). An important factor is the non-verbal communication between driver and other road users, such as eye-contact or a hand gesture (Guéguen, Meineri, & Eyssartier, 2015; Malmsten Lundgren et al., 2017). However, such communication may not be available in the same way or would even be impossible when there is no driver present in the AV. How this would affect the interaction between cyclists and AVs is still unclear and has until recently been overlooked in the literature.

Microscopic simulations of interactions between AVs and cyclist show that a decrease in conflicts between AVs and cyclists can be expected. This is assuming a penetration rate of 100% of AVs. Furthermore, the severity of conflicts is also expected to decrease. However, before reaching a 100 % penetration rate the safety of cyclists should be considered when interacting with AVs (Tafidis, Pirdavani, Brijs, & Farah, 2019). However, before reaching a 100% penetration rate AVs need to be able to perform in a mixed environment. Initial video analysis of footage recorded during the CityMobil2 demonstrations shows how cyclist adapt to AVs. Where possible cyclists avoided getting to close to AVs. However, when it was not possible to keep distance, cyclists stayed close to AVs instead of waiting for the AV to pass. This could be seen as risky behavior (Madigan et al., 2019). In line with these results, Bjørnskau et al (2019) found that cyclists adapted their behavior. Over time, cyclists gave the right of way less to AV shuttles and overtook the shuttles more.

Hagenzieker, et al. (2016, 2019) performed a small-scale photo study to investigate whether there is a difference in the expectations and behavioural intentions of cyclists when interacting with an AV at an intersection as compared to a contemporary vehicle (CV) using signs stating that the vehicle was automated mounted on several places. Overall, the researchers found that the way the vehicles are perceived depended on the scenario. Given the fact that AVs are expected to be safer, it is surprising that no clear preference for the AVs over the CV was found. The authors explain that the balanced results for AVs and CVs indicate that the participants have a conservative and cautios disposition towards AVs.

In contrast with previous findings, a small preference was found in favour of AVs in a follow-up study building on Hagenzieker's and colleagues (2016) design (Rodríguez Palmeiro, van der Kint, Hagenzieker, van Schagen, & de Winter, 2018). AVs were perceived as more likely to stop for the cyclist. When interacting with AVs, participants stated that they felt more likely to be noted and were more confident that the car would stop for them compared to the CV. Furthermore, the results of the administered trust in self-driving technology questionnaire were compared to the answers on the scenarios. The findings show that participants with more trust in AVs reported to be more noticed by the AVs, that AVs would stop for them, and decided to continue cycling more often than participants with less trust.

Finally, another study on cyclists crossing intentions was performed using animated videos (Vlakveld & Van der Kint, 2018). The videos were made from the perspective of the cyclists and contained three types of vehicles: automated, automated and disclosing its intentions, and a CV. Furthermore, five situations were presented with the use of the videos. The researchers report that cyclists yielded more when the vehicle was automated and less when the vehicle was automated and displayed its intention, as compared to the CV. In contrast to the previous two studies, the cyclist yielded more for both types of automated vehicles if they received the negatively framed information about AVs. The researchers explain that the effect of an instruction video may be more effective in affecting the participants than written instructions. In addition, a negative correlation was found between yielding and trust in AVs. So, when participants experienced low trust in AVs they yielded more. All in all, most of the results of this study are in line with the previous two. Cyclists act carefully when interacting with AVs. Also, trust seems to be an important factor that can affect cyclists' decisions.

The present study aims at gaining insights into the crossing intentions of cyclists while interacting with AVs as compared to CVs. Our main research question was the following: *How does the physical appearance of a vehicle affect the crossing intentions of cyclists?* We also investigated how the vehicles' motion cues intentions and how the existing priority regulations affected cyclists' crossing intentions. In contrast to the presented studies, this study made use of 360° video-based virtual reality (VR) to provide control over the interaction. Psychological factors such as trust in AVs and perceived risk and perceived behavioral control were studied to provide insights into how these factors are affected by AVs. Vehicle factors - vehicle speed and gap size were also included. Furthermore, the right of way was included in our studies.

4.2 **Research Methodology**

A repeated measures experiment was designed where each participant completed 16 scenarios using a 360° video-based VR method. The 16 scenarios were created considering a set of 4 variables each with 2 levels as described in Table 5. The gap size was calculated as the time needed before the vehicle crossed the path of the cyclist and was achieved by stopping the video at the desired time gap. The 16 scenarios were completed twice per participant (session 1 and session 2). Before the second session started, the participants were told explicitly that there were two types of vehicles present in the experiment and which vehicle of the two was a CV and which was an AV. That ensured there was a complete data set where the participants knew they were interacting with an AV. The two vehicles are illustrated in Figure 8.

Figure 8. Appearance of AV (left) and CV (right).

Table 5. Variables included in the VR experiment.

Variable name	Levels	Annotation	Explanation
Vehicle type	2	AV	Automated Vehicle
		CV	Conventional Vehicle
Vehicle speed	2	20	Vehicle driving speed 20 km/h
		30	Vehicle driving speed 30 km/h
Gap size	2	Small Gap (SG)	Gap between vehicle and cyclist was 0.5 seconds/ 2.8 m (V = 20)/ 4.2 m (V = 30)
		Large Gap (LG)	Gap between vehicle and cyclist was 2 seconds/ 11.1 m (V = 20)/ 16.7 m (V = 30)
Priority to the cyclist	2	Yes	Cyclist had priority over the vehicle
		No	Vehicle had priority over the cyclist

4.2.1 Apparatus

All the videos were recorded using the Nikon Keymission 360. The camera has two lenses making it possible to film in 360° . The videos had a resolution of 3480x2160 pixels with a 24 frames per seconds. A special camera mount (i.e. GoPro mouth mount) was used that allowed to record videos from the height of one’s chin. The videos were shown to the participants using an iPhone 7 with a screenresolution of 1334x750 pixels and using a consumer app (VR Media Player) downloaded from the App Store and a consumer level head-mounted displaysmartphone holder such as the Samsung Gear. The intersection on which the scenarios were filmed was a quiet rural crossing with nothing obstructing the view of the car. A screenshot of one of the videos can be seen in Figure 9. The videos represented a cyclist riding towards a crossing while a vehicle was moving towards the cyclist from one of the side directions. The video stopped at the critical moment (i.e. when the desired gap size was reached). This stopping point (determining the gap size) was based on the needed braking distance for the cyclists in case she/he would decide to stop, so that participants would still be able to stop (CROW kennisbank, 2018). The participants were asked what they would do: 1) continue cycling, 2) cycle faster or 3) slow down. They were free to imagine how much they would change their speed if they chose to cycle faster or to slow down. Slowing down could also include the option to come to a complete stop. The participants had to answer verbally and was noted by the researcher. Every participant watched all 16 different scenarios per session. The videos were randomized and three versions were made.

4.2.2 Location

Two locations were tested before choosing the one used for the experiment. Both locations contained an intersection of two roads. Two of the intersections were in urban areas with traffic.

Other road users appeared on the videos often. This could have an additional (in this case undesired) effect on the participants. Furthermore, the urban environment contained obstacles often blocking the view of the car. Thus, we decided against using these locations. We searched for an intersection with the least amount of obstacles and the lowest amount of traffic for our filming location. Other requirements were: The asphalt had to be smooth to reduce shaking in the videos, and without priority markings present at the location. A location in a rural area was found that met our requirements and was used in the final videos.

Figure 9. Screenshots of the 360° videos with the vehicle at different distances.

4.2.3 Pilot Studies

Three pilot studies were conducted before setting the final experiment. The first pilot study was to attain a realistic cycling speed. The speeds tested were 12 km/h, 15 km/h and 18 km/h as these are average cycling speeds (KiM, 2016). Ten out of sixteen participants reported that, to them, a cycling speed of 15 km/h felt the most realistic of all the three. In the second pilot study the speed of the vehicle, the gap sizes, and the vehicle's color were investigated. The speed of the vehicle (i.e. 20 and 30 km/h) was chosen for practical reasons. It was important that the vehicle would be visible (in the VR) for the cyclist to be able to notice it. This was not possible if the speed of the vehicle was higher than 30 km/h. Similarly, the gap sizes were chosen based on what was found to be the most realistic to the participants using the VR in the pilot studies. Besides gap sizes of 0.5 and 2.0 seconds, also a gap size of 4.0 seconds was tested but it did not result in a variation in the crossing intention among the participants of the pilot study since the vehicle would be too far out of sight of the cyclist. Therefore, only gap sizes of 0.5 and 2.0 seconds were used. A gap size of 0.5 seconds was tested as this was the shortest possible gap size in which the cyclist could cross the road without accelerating. This gap size proved to elicit variation in the crossing intentions of the pilot study and was therefore maintained. Furthermore, a dark vehicle was hard to distinguish in the recordings and therefore a light color vehicle was chosen. In the third pilot study, the vehicle appearances and the priority markings were chosen. The vehicle used in the recordings was a white BMW 5-series, since it was comparable in size to the AV (which in this study was the Waymo Fiat Chrysler as can be seen in figure 8). As can be seen in figure 9 the white colour was clearly visible. Since AVs are not widely used yet, it was difficult to get a real AV vehicle for the recordings. Therefore, the AV was created via video editing which also ensured that the AV had the same size and speed as the CV, because it was placed over the CV and tracked to its exact movements. Figure 8 shows the appearance of both vehicles in the videos. The software used to edit was Adobe Photoshop, Adobe Premiere Pro and Adobe After Effects. The Waymo Fiat Chrysler turned out to be the most realistic appearance compared to the Google Firefly of an AV in the video and was therefore used in the experiment.

To simulate priority for the vehicle, video edited priority markings were tested, but they proved to be hard to see. Therefore, the vehicle approached the cyclists from the right in half of the videos, thus in these cases it had the right of way. To simulate priority to the cyclists, the vehicle approached the cyclists from the left.

4.2.4 Sample

To collect the data, 47 participants (24 males; 23 females) took part in the experiment. All tThe participants had to be 18 years old or older and be able to ride a bicyclecycle in daily life. Participants had to be able to see clearly without glasses as this could not be used while wearing the head mounted display. Since the experiment was conducted at the TU Delft, most of the participants were (former) students. As age was found in the literature to have an influence on the crossing behavior of cyclists and the set of participants was relatively small, a homogenous age was chosen for all the participants, so that the differences in their intentions were not due to differences in their age (Bernhoft & Carstensen, 2008; Demiroz, Onelcin, & Alver, 2015). The participants were informed that the experiment was about crossing behavior of cyclists. Automated vehicles were not mentioned in order not to influence or bias their crossing decisions in the first session. We also tested whether they participants noticed any difference between the vehicles. The experiment was approved by the ethical committee of the Delft University of Technology.

4.2.5 Questionnaires

All participants filled in a set of questionnaires before, during and after the experiment. The first survey contained questions about the participants' demographics and the pedestrian behavioral scale (PBS) adjusted for cyclists (Granié, Pannetier, & Guého, 2013). This questionnaire included items such as '*Cycle on the road instead of a bicycle lane*', '*See a small gap in traffic and "go for it"*'', and '*Think it is OK to cross safely, but a car is coming faster than you thought*'. One had to respond on a scale from 1 (never) to 5 (often) how often they performed certain behaviors. So, the higher the score the riskier one behaves. The results of this questionnaire were used to divide the group in the lower risk group and a higher risk group by dividing the participants based on the mean score of the whole group.

Furthermore, the level of trust in AVs was measured per participant using the trust in AVs scale (Núñez Velasco et al., 2018; Payre, Cestac, & Delhomme, 2016). This scale contained questions such as '*Globally, I trust the automated vehicle'*, '*I trust the automated vehicle to have seen me*', and '*I trust the automated vehicle to drive safe*'.

To determine how the participants experienced the VR environment, the Presence Questionnaire has been used (Jerome, 2009). It contained items such as '*How natural did your interactions with the environment seem?*' '*How completely were your senses engaged in this experience?*', and '*How completely were your senses engaged in this experience?*'.

A side-effect of using VR is that participants may get sick due to visually induced motion sickness (Bos, Bles, & Groen, 2008; Lubeck, Bos, & Stins, 2015). Although most people do not experience this, previous research has shown that not everybody can tolerate the virtual environment (Deb et al., 2017). To ensure participants did not suffer from motion sickness, they filled in a misery scale (MISC) before, during and at the end of the experiment (Van Emmerik, De Vries, & Bos, 2011). The participants could score to what extent they experienced simulation sickness symptoms on a scale from 0 to 10 with 0 being not experiencing any symptoms and 10 being extremely simulation sick. If their scores increased significantly during the experiment, the experiment was paused and we checked with the participant whether he/she was able to continue.

Perceived behavioral control (PBC) was measured using 2 items; '*For me, crossing the road in this way would be...*', and '*I believe that I have the ability to cross the road in this way...*' (Zhou et al., 2009a). PBC was measured for the BMW and the Waymo vehicle after session 1 if participants indicated to have noticed a difference between the vehicles, otherwise the questions were skipped. After session 2, all the participants answered the PBC items.

Perceived Risk (PR) was a 1 item scale that was applied using the same procedure as PBC. The item was the following: '*Crossing the road in this situation would be...*'. Both PBC and PR were answered using a 7-point Likert scale. The scale was inverted for PBC. So, the higher the score the less PBC one experienced.

4.2.6 Procedure

At the very beginning, the participants had to sign an informed consent form before the experiment could begin. Then, the participants filled in a survey. The survey contained questions about their demographics and regarding their vision (eye sight). Following this, the adapted pedestrian questionnaire and the MISC were filled in. Then, they watched the first 8 videos of session 1, which took 3 minutes in total. A MISC questionnaire was filled in once again and then the last 8 videos of session 1 were shown. After the first session, the participants were asked to fill in the MISC for the third time. Following this, they were asked whether they had perceived any difference between the vehicles, about their perceived risk and their perceived behavioral control per vehicle, and they were asked to report how much they knew about AVs. Furthermore, they filled in the Trust in AVs questionnaire. Then, they were told about the AV and the CV types used in the experiment, by showing pictures of the vehicles. In session 2, the same videos were shown. The first 8 videos were presented. Then, a MISC was filled in. Finally, the last 8 videos of session 2 were shown. The final MISC was filled in after session 2. At the end, the participants completed the Presence questionnaire before they were debriefed. In total, the experiment lasted 60 minutes, and each session (i.e., 8 scenarios) took 3 minutes.

4.3 Results

We first present descriptive statistics followed by the overall results of the multinomial logistic mixed regression (MLMR) model regarding the crossing intentions. In addition, the results of the Perceived behavioral control (PBC) and Perceived risk (PR) are presented. Then, the results of the MLMR models per session are displayed. Finally, the results of the VR assessment are reported.

4.3.1 Descriptive statistics

Forty-seven individuals (24 males; 23 females) participated in the experiment. Their mean age was 24.0 (*SD* = 2.7). All the participants had normal or corrected to normal vision. Forty-six participants cycled daily. Most of their daily cycling trips lasted between 15 to 60 minutes accumulated. Almost all, 43, stated to know what an automated vehicle was. On a scale from 1 to 6 , the self-reported mean score on how much one knew about automated vehicles – 1 is ‘almost nothing’ and 6 ‘a great deal’ – was 3.4 (*SD* = 1.2). No statistically significant difference was found between genders, *t*(45) = -0.16; *p* = .87. Thirty-five of the participants noticed a difference between the two vehicles. However, only five thought that some of the vehicles were automated in session 1.

The Trust in AVs mean score was 4.7 (*SD* = 0.9) on a 7-point Likert scale – 1 means ‘low trust’ and 7 means ‘high trust’ –, and no statistically significant difference was found between genders (males *M* = 4.7, *SD* =1.0; females *M* = 4.6, *SD* =0.9), *t*(45) = 0.53; *p* = .60. The participants stated whether they had more, less or equal trust in AVs as compared to CVs. Six stated that they had more trust in AVs, 14 stated to have less trust in AVs and 27 stated that they trusted them equally. The trust in AVs score differed significantly between the groups, *F*(2, 44) = 8.21, *p* = .001. The group that trusted the AVs more than CVs (*M* = 5.4, *SD* = 0.5) and the group that trusted them equally (*M* = 4.8, *SD* =0.8) scored significantly higher on the Trust in AV scale than the group that had less trust in AVs (*M* = 4.0, *SD* = 1.0) as revealed by a Bonferroni post hoc test. Further, the participants were divided into two groups based on their score on the adapted Pedestrian Behavior Scale (PBS); those that scored higher than the total mean were labeled ‘higher risk group’ and those that scored lower than mean were labeled ‘lower risk group’. The mean score on the adapted PBS was 2.7 (*sD* = 0.6) on a scale from 1 to 7, 24 participants (12 females and 12 males) were labeled as lower risk group (*M* = 2.3, *SD* = 0.3) and the other 23 as higher risk group (*M* = 3.1, *SD* = 0.4). The difference in PBQ score between groups was statistically significant, *t*(45) = -7.10; *p* < 001. No difference was found in Trust in AVs score between the higher risk group (*M* = 4.9, *SD* = 0.7) and lower risk group (*M* = 4.4, *SD* =1.1), *t*(45) = -0.16; *p* = .87.

4.3.2 Crossing intentions

Each of the 47 participants watched 32 videos and made just as many crossing intention decisions. Therefore, the data set consisted of 1504 choices. In four occasions a participant missed the vehicle in the video and could therefore not answer, these occasions were eliminated, so that the total data set contained 1500 decisions. To analyse which factors influenced participants’ crossing intentions, multinomial logistic mixed regression models were estimated. A mixed model with a random intercept was chosen to capture the correlation between the decisions made in different scenarios by the same participant (Lund Research Ltd, 2018). An unstructured covariance matrix has been chosen for the error structure (Kincaid, 2005; Singer, 1998). The multinomial logistic mixed regression model was estimated using maximum likelihood.

The participants were given three options in the experiment: continue cycling, cycle faster and slow down. In the models 'continue cycling' was chosen as the reference category to which slow down and cycle faster were compared to. The variable time gap size was converted to distance gap, since people select a gap mostly based on distance, instead of a gap in time (J.P. Núñez Velasco et al., 2019; Oxley et al., 2005). Furthermore, a gap size measured in meters enables to remove speed from the equation, which allows to measure the effect of speed and gap size separately (Oxley et al., 2005). Trust in AVs, gender and speed have been omitted from the succeeding models as they proved insignificant in all the models. Also, the random intercept was found to be insignificant in all of the models and was therefore omitted from the models.

As shown in Table 6, participants' intentions to cross did not differ significantly between the two vehicles. When the gap size was 4.2 meters or smaller the participants chose to slow down significantly more compared to continue cycling. The effect size was very large for the case of slowing down. Cycling faster was chosen significantly more compared to continue cycling only when the vehicle was 2.8 meters from the cyclist. The effect size was relatively large. If the cyclists had priority they chose significantly less to slow down or to cycle faster compared to continue cycling. The effect was large when it comes to slow down and large when choosing to cycle faster.

The lower risk group decided to slow down and to cycle faster significantly more than the higher risk group. The effect size was medium for both. The participants were divided into groups based on their stated trust in AVs as compared to CVs. They were divided into three groups, the ones who stated they trusted AVs more than CVs, the ones who trusted AVs less than CVs and the ones who said there was no difference for them. However, no statistically significant difference was found between the three groups. The interaction between vehicles and stated trust showed a significant effect but only on the probability to slow down and only when the vehicle was a CV. When the participants had less trust in the AV as compared to the CV, then they slowed down less. The effect size was medium (Chen, Cohen, & Chen, 2010).

Table 6. Results of the Crossing Intention Multinomial Logistic Mixed Regression (MLMR) Model for both sessions combined.

Fixed Coefficients	B (SE)	Odds Ratio	*95% CI*	*p*
Slow down				
Intercept	-0.74(2,22)	0.48	[0.01,37.50]	.73
Vehicle type (1 = CV, 2*= AV)	-0,19(0,19)	0.83	[0.57,1.21]	.33
Gap distance (meters; 1 = 2.8 m, 4*= 16.7 m)	2.36(0.21)	10.55	[7.03,15.85]	<.001
Gap distance (meters; 2= 4.2 m, 4*= 16.7 m)	2.39(0.20)	10.92	[7.31,16.31]	<.001
Gap distance (meters; 3 = 11.1 m, 4*= 16.7 m)	0.10(0.21)	1.01	[0.73,1.65]	.65
Priority to cyclist (1 = yes, 2*= no)	-2.03(0.15)	0.13	[0.10,0.17]	<.001
Risk group(1 = low, 2* = high)	0.56(0.15)	1.76	[1.31,2.37]	<.001
Stated Trust (1 = More, 3* = No difference)	-0.30(0.32)	0.74	[0.40,1.38]	.34
Stated Trust (2 = Less, 3* = No difference)	-0.10(0.23)	0.91	[0.58,1.42]	.67
Vehicle * Stated Trust (CV * More)	0.76(0.44)	2.14	[0.90,5.10]	.09
Vehicle * Stated Trust (CV * Less)	-0.75(0.33)	0.47	[0.25,0.90]	.02
Cycle faster				
Intercept	-0.23(2.22)	0.74	[0.01,62.14]	.92
Vehicle type (1 = CV, 2*= AV)	0.26(0.19)	1.29	[0.89,1.88]	.18
Gap distance (meters; 1 = 2.8m, 4*= 16.7 m)	1.05(0.20)	2.86	[1.91,4.27]	<.001
Gap distance (meters; 2= 4.2 m, 4*= 16.7 m)	0.31(0.21)	1.36	[0.91,2.04]	.14
Gap distance (meters; 3 = 11.1 m, 4*= 16.7 m)	0.02(0.20)	1.02	[0.69,1.50]	.93
Priority to cyclist (1 = yes, 2*= no)	-0.99(0.15)	0.37	[0.28,0.50]	<.001
Risk group(1 = low, 2* = high)	0.30(0.15)	1.35	[1.00,1.81]	.05
Stated Trust (1 = More, 3* = No difference)	-0.44(0.32)	0.65	[0.34,1.21]	.17
Stated Trust (2 = Less, 3* = No difference)	-0.13(0.23)	0.88	[0.56,1.39]	.59
Vehicle * Stated Trust (CV*More)	-0.10(0.45)	0.90	[0.37,2.18]	.82
Vehicle * Stated Trust (CV*Less)	-0.56(0.33)	0.57	[0.30,1.08]	.08

Note: * = Reference category. Odd ratios size: 1.68 = small , 3.47 = medium, 6.71 = large (Chen, Cohen, & Chen, 2010).

4.3.3 Perceived Behavioral Control and Perceived Risk

The participants answered questions per vehicle about their perceived behavioral control (PBC) and perceived risk (PR). Only participants who noticed a difference between vehicles in the first session (N = 35) answered the PBC and PR questions. All the participants filled this questionnaire after session 2 since they were explicitly told about the two types of vehicles before session 2 started.

The participants reported a PBC score of 5.0 (*SD* = 0.8) before session 2 and 5.1 (*SD* = 1.0) after, thus no significant difference. For the PR score it was respectively, 4.6 (*SD* = 0.7) before and 4.9 (*SD* = 0.9) after. The mean PBC scores per vehicle type per session can be found in table 7. There were no significant differences between the sessions or vehicles score pairs', except the PR scores of CVs and the scores of AVs in session 1, *t*(34) = -3.02; *p* = .005, and the PR scores of CVs before and the scores in session 2, *t*(34) = -3.76; *p* = .001. The other test statistics have been left out for the sake of clarity.

Table 7. Mean PBC and PR scores per vehicle per session.

	Session 1		Session 2	
	AV	CV	AV	CV
PBC	5.2 (*SD* = 1.0)	4.8 (*SD* = 1.2)	5.0 (*SD* = 1.1)	5.2 (*SD* = 1.3)
PR	5.0 (*SD* = 1.1)	4.2 (*SD* = 1.0)	4.7 (*SD* = 1.2)	5.0 (*SD* = 1.2)

4.3.4 Models per session

Only 14% thought they had seen an AV in the first session, so it is interesting to analyse the differences between the sessions before and after participants were told one vehicle was an AV. Therefore, two separate models were created based on the data of only session 1 or 2. Also, we added the respective PBC and PR scores as factors to the model to see how they perform as predictors of the participants' crossing intentions. As seen in Table 8, both models performed better than the full model based on the data from both sessions together. The model with the data of session 1 had the best performance of the three models.

Table 8. Performance of the models.

Model	-2 LL	AIC	BIC
Full model (table 2)	10970.2	10974.2	10984.8
Session 1 model (table 4)	4095.7	4099.8	4108.3
Session 2 model (table 5)	5407.7	5411.7	5420.9

In Table 9 the models' results of session 1 and session 2 can be found. Vehicle type remained an insignificant predictor of the crossing intentions. Gap distance was a significant predictor of cyclists slowing down. It had a very large positive effect in both sessions. However, gap distance had only a significant positive effect on cycling faster in session 2. As shown in Table 9 the effect size is large in the case of 2.8 meters and a medium effect size in the case of 4.2 meters as compared to 16.7 meters. To have priority had a significant negative effect on the decision to slow down and cycle faster as compared to continue cycling. The effect size was very large for the slow down option and medium to large for the cycle faster option. Those who reported that they trust the AV more than the CV had significantly lower intentions to slow down or cycle faster compared to continue cycling in session 2. Both effect sizes were large. Interestingly, one's knowledge about AVs had only a significant negative effect to slow down or cycle fatser compared to continue cycling in session 1. The effect was small. One's PBC when interacting with a CV had a significant negative effect on the decision to slow down as compared to continue cycling in session 1. The effect size was small. One's PBC when interacting with an AV was only significant in session 2. Furthermore, it had positive effects on both choice options. The effect size was medium. In addition, one's PR when interacting with an AV was only significant in session 2, too. The effect sizes were medium and negative, in this case. Finally, when participants have less trust in AVs, and are interacting with a CV, they chose to continue cycling more as compared to slow down and cycle faster in session 2. The effect size was large.

Table 9. Results of the crossing intentions MLMR Model for both sessions.

Fixed Coefficients	Session 1		Session 2	
	Odds Ratio	*95% CI*	Odds Ratio	95% CI
Slow down				
Intercept	12.31	[0.10,1578.9]	3.82	[0.04,349.3]
Vehicle type (1 = AV, 2^+ = CV)	0.64	[0.35,1.17]	1.00	[0.59,1.70]
Gap distance (meters; 1 = 2.8 m, 4^+ = 16.7 m)	8.35***	[4.27,16.34]	13.32***	[7.50,23.67]
Gap distance (meters; 2= 4.2 m, 4^+ = 16.7 m)	10.40***	[5.34,20.22]	12.77***	[7.26,22.45]
Gap distance (meters; 3 = 11.1 m, 4^+ = 16.7 m)	1.07	[0.54,2.11]	1.11	[0.63,1.97]
Priority to cyclist (1 = yes, 2^+ = no)	0.16***	[0.10,0.25]	0.11***	[0.08,0.17]
Risk group(1 = low, 2^+ = high)	1.46	[0.84,2.55]	1.66*	[1.07,2.60]
Stated Trust AV as compared to CV(1 = More, 3^+ = No difference)	0.66	[0.23,1.89]	0.39	[0.15,1.01]
Stated Trust AV as compared to CV(2 = Less, 3^+ = No difference)	0.50	[0.22,1.10]	0.77	[0.36,1.68]
KnowledgeAVs	0.77*	[0.62,0.95]	1.03	[0.86,1.23]
PBC CV	0.73*	[0.53,1.00]	0.79	[0.56,1.11]
PR CV	1.11	[0.78,1.57]	0.89	[0.65,1.24]
PBC AV	0.87	[0.57,1.35]	1.69*	[1.11,2.58]
PR AV	1.00	[0.69,1.46]	0.54***	[0.39,0.75]
Vehicle * Stated Trust(CV*More)	2.26	[0.69,8.86]	2.09	[0.62,7.11]
Vehicle * Stated Trust(CV*Less)	1.32	[0.44,3.98]	0.31*	[0.13,0.78]
Cycle faster				
Intercept	23.66	[0.18,3050.2]	3.72	[0.04,337.0]
Vehicle type (1 = AV, 2^+= CV)	1.34	[0.73,2.47]	1.28	[0.75,2.19]
Gap distance (meters; 1 = 2.8 m, 4^+= 16.7 m)	1.44	[0.74,2.80]	4.84***	[2.74,8.54]
Gap distance (meters; 2= 4.2 m, 4^+= 16.7 m)	0.97	[0.50,1.90]	1.75	[0.98,3.11]
Gap distance (meters; 3 = 11.1 m, 4^+= 16.7 m)	0.95	[0.51,1.80]	1.12	[0.65,1.93]
Priority to cyclist (1 = yes, 2^+= no)	0.39***	[0.25,0.63]	0.37***	[0.25,0.56]
Risk group(1 = low, 2^+ = high)	1.22	[0.70,2.12]	1.43	[0.92,2.22]
Stated Trust AV as compared to CV(1 = More, 3^+ = No difference)	0.92	[0.32,2.61]	0.24**	[0.09,0.62]
Stated Trust AV as compared to CV(2 = Less, 3^+ = No difference)	0.61	[0.27,1.36]	0.84	[0.38,1.83]
KnowledgeAVs	0.88	[0.71,1.09]	1.02	[0.85,1.22]
PBC CV	0.91	[0.66,1.25]	0.78	[0.55,1.10]
PR CV	0.78	[0.55,1.11]	0.80	[0.58,1.11]
PBC AV	0.84	[0.55,1.29]	2.09***	[1.37,3.20]

PR AV	0.99	[0.68,1.45]	0.53***	[0.38,0.74]
Vehicle * Stated Trust(CV*More)	0.51	[0.13,2.06]	1.24	[0.36,4.32]
Vehicle * Stated Trust(CV*Less)	1.18	[0.39,3.52]	0.34**	[0.14,0.84]

Note: $^{+}$ = Reference category. Odd ratios size: 1.68 = s , 3.47 = m, 6.71 = l (Chen, Cohen, & Chen, 2010). $^{*}p \leq 0.05$; $^{**}p \leq 0.01$; $^{***}p \leq 0.001$

Performance of the VR method

The results of the Presence Questionnaire pointed towards participants experiencing the VR environment as realistic (Table 10). The lowest score was found for the quality of the interface (i.e. 2.67). Overall, the scores as reported in Table 10 are comparable to previous research (Núñez Velasco et al., 2019). Furthermore, the score on the MISC (Table 11) were relatively low meaning that participants experienced few symptoms of simulation sickness. The scores were slightly increasing over time. The range of the self-reported scores was 0 to 10, with 10 being chosen only thrice.

Thirty-eight participants felt that crossing the road in the VR was different as compared to real life. Twenty-eight participants felt ‘slightly safer’ to ‘safer’ as compared to real life. Seven participants did not experience any difference and twelve felt slightly unsafer in the VR environment as compared to real life.

Table 10. Results of the Presence Questionnaire (1 (low presence) – 7(high presence)).

	Involvement	Adaptation/ Immersion	Interface quality	Total mean
Mean	4.69	5.20	2.67	4.47
SD	0.57	0.81	1.00	0.64

Table 11. Results of the MISC (0 (no symptoms) – 10 (vomiting)).

	MISC Baseline	MISC 1 Session 1	MISC 2 Session 1	MISC 1 Session 2	MISC Final
Mean	1.47	1.89	1.85	1.94	2.26
SD	0.98	2.18	1.02	1.39	1.82

4.4 Discussion

The main aimgoal of this research was to determine what the differences are in crossing intentions of cyclists when interacting with AVs compared to CVs. To this end AVs were simulated in the present experiment. In addition, the perceived realism of 360° video-based VR for research purposes was assessed for cyclists’ crossing intentions. The variables vehicle type, the gap between the cyclist and vehicle, right-of-way priority, trust in AVs, perceived behavioral control, and perceived risk were included as potential factors that could affect the crossing intentions. This resulted in two sessions each of total 16 scenarios divided by an intervention in which the participants were told that the Waymo Fiat Chrysler vehicle was an AV. The scenarios were presented to 47 individuals by using a smartphone based virtual reality. The main findings of both sessions were the following. The distance between the cyclist and the vehicle at an intersection and whether having right of way are the primary factors influencing cyclists’ crossing intentions. This is in accordance with findings on vulnerable road users’ crossing intentions (Núñez Velasco et al., 2019; Oxley et al., 2005). Participants choose to adapt their speed (i.e. cycling faster or slowing down) when the gap size was shorter. This indicates that the cyclists did not feel safe and therefore intervened by adapting their cycling speed when the gap sizes were short. Speed of the approaching vehicle was not of influence on the crossing intentions. This points towards gap size (measured in distance) being the more important factor of the two. When the participants had the right of way, they preferred to continue cycling instead of adapting their cycling speed. So, the cyclists felt safer when they had the right of way and decided not to adapt their speed relying on the vehicle to do so. Also, the fact that less effort is required to continue cycling as compared to cycle faster and to slow down, could be a reason why the participants preferred to continue cycling. It could be that the participants triedy to minimize effort while maximizing safety. So, if the situation is safe one would prefer not to adapt their speed in contrast to when the situation is unsafe. The vehicle appearance and vehicle automation did not have a significant effect on the crossing intentions. This was in accordance with the literature on previous studies on cyclists' interactions with AVs (Hagenzieker et al., 2019; Rodríguez Palmeiro et al., 2018). No clear preference was found for the AV in contrast to what could be expected because AVs ought to be safer. The participants may not perceive the AV as safer than the CV and therefore interact with both vehicles in the same manner. Secondly, this could indicate that cyclists use their learned strategies even when interacting with a new type of vehicle. Either way, the participants did not perceive the need to interact with AVs differently than with CVs.

In accordance with Núñez Velasco, et al. (2019), the Trust in AVs in itself was not a significant predictor of the crossing intentions. However, participants' statements whether they trusted AVs more or less as compared to CVs was a significant predictor of the crossing intentions. Thus, the absolute trust does not capture the relative value of trust between vehicles. One could score highly in the Trust in AVs scale but have more trust in CVs, still. The limitation of the trust scale used in this study is that it is 1 item only. A scale consisting of multiple items comparing the trust in both types of vehicles could be a better predictor and explain cyclists' intentions better.

The main findings regarding session 2 were the following: Participants who were categorized in the lower risk group chose to cycle faster or to slow down more often than the higher risk group. Curiously, this was only the case in session 2 where they knew that they were interacting with an AV in addition to a CV. The group that had more trust in AVs decided to continue cycling more often overall as compared to the other two options involving speed adaptation. This indicates that they might have felt safer and therefore did not adapt their speed. In Rodríguez Palmeiro, and colleagues study they also found a relation between trust and perceived safety when interacting with AVs (Rodríguez Palmeiro et al., 2018). However, we found that cyclists who stated that they trust AVs less (than a CVs) decided to continue cycling more as compared to slowing down and cycling faster when interacting with a CV. This means that those cyclists perceived less risk when they were interacting with a CV than with an AV and thus, did not feel the need to adapt their speed. In contrast to participants choosing riskier answers (e.g. continue cycling instead of slowing down) when scenarios were presented that contained AVs, as found by Rodríguez Palmeiro, and colleagues (Rodríguez Palmeiro et al., 2018). So, instead of changing their intentions (by adapting their speed) when interacting with AVs, they chose to not adapt their intentions when they interacted with a CV. PR of AVs had a significant negative effect which means that those that perceived a higher risk when interacting with AVs decided to slow down and to cycle faster less. The opposite is true for PBC when interacting with an AV. When the participants experience more perceived behavioral control when interacting with AVs they decided to adapt their behavior more, overall. Overall, a positive relation was found between adaptation of speed and PBC and a negative between adaptation of speed and PR. Lastly, the effect of the gap size became even more pronounced in session 2. So, knowing that one of the vehicles was automated, increased the effect of the gap size on the crossing intentions. It could be that the knowledge is not the reason the effect size increases but the repetition of the task. Participants could have become better at deciding when to cross based on the gap size. To examine this effect, the data of the first session was split in two halves and the crossing intention model was estimated for each part of the data separately and the results were compared regarding the effect of gap size on crossing intentions and found that the effect was larger in the second half of session 1 (for example odds ratio (OR) = 6.6 versus OR = 10.3 for distance gap in the first and second half, respectively) proving that it is a learning effect.

The 360° video-based VR was useful as a research method to investigate the crossing intentions of cyclists. Participants did not suffer from motion sickness and everyone was able to finish the experiment. Furthermore, the scores on the Presence questionnaire were similar to those previously found (Núñez Velasco et al., 2019). Even though 60% of the participants indicated they felt safer in VR than in real life, their crossing decisions still showed a trade-off, and nobody crossed in all scenarios. It is unclear why some of the participants reported to feel less safe in VR. A reason could be that they felt that in real life they do not experience these kinds of critical scenarios often. Future research could focus on creating insights into this. The recording angle of the videos, from the viewing perspective of the cyclist was found very realistic by the participants and the recordings were steady and comfortable to watch. However, due to the use of a head mounted smartphone holder that places the display in front of ones eyes, no peripheral vision could be used by the participants. This could had the implication that the cyclists had to look at the vehicles to be able to see them. In real life, the peripheral vision could have provided the cyclists with information about the vehicles' location and speed without the cyclists having to have looked at it. More research could focus on how the lack of peripheral vision impacts cyclists' crossing intentions and behavior. Furthermore, research should focus on the comparison of VR and real world cyclists' behavior studies to increase our understanding of the transferability of results in VR studies to the real world.

4.5 **Conclusions**

The answer to our main research question 'How does the physical appearance of a vehicle affect the crossing intentions of cyclists?' is the following: Cyclists' do not seem to have different behavioural intentions when interacting with AVs as compared to when they interact with CVs. The vehicle appearance and type were not found to influence their intentions. The answers to the other research questions 'How do the vehicles' motion cues intentions and the existing priority regulations affected cyclists' crossing intentions?' are the following: The gap size and the right of way were the most important factors affecting cyclists' crossing intentions. The vehicle appearance and type were not found to influence their intentions. Cyclists' do not seem to have different behavioural intentions when interacting with AVs as compared to when they interact with CVs. Participants' statements whether they trusted AVs as compared to CVs was found to be a stronger predictor of the crossing intentions than the Trust in AVs by itself. The 360° video-based VR method was useful as a research method to investigate the crossing intentions of cyclists.

Chapter 5 - Will Pedestrians Cross the Road before an Automated Vehicle? The Effect of Drivers' Attentiveness and Presence on Pedestrians' Road Crossing Behavior[4]

Abstract

The impact of automated vehicles (AV) on pedestrians' crossing behavior has been the topic of some recent studies, but findings are still scarce and inconclusive. The aim of this study is to determine whether the drivers' presence and apparent attentiveness in a vehicle influences pedestrians' crossing behavior, perceived behavioral control, and perceived risk, in a controlled environment, using a Head-mounted Display in an immersive Virtual Reality study. Twenty participants took part in a road-crossing experiment. The VR environment consisted of a single lane one-way road with car traffic approaching from the right-hand side of the participant which travelled at 30 kmph. Participants were asked to cross the road if they felt safe to do so. The effect of three driver conditions on pedestrians' crossing behavior were studied: Attentive driver, distracted driver, and no driver present. Two vehicles were employed with a fixed time gap (3.5 s and 5.5s) between them to study the effects of time gaps on pedestrians' crossing behavior. The manipulated vehicle yielded to the pedestrians in half of the trials, stopping completely before reaching the pedestrian's position. The crossing decision, time to initiate the crossing, crossing duration, and safety margin were measured. The main findings show that the vehicle's motion cues (i.e. the gap between the vehicles, and the yielding behavior of the vehicle) were the most important factors affecting pedestrians' crossing behavior. Contrary to expectations, the no driver condition did not have a significant effect on pedestrians' crossing behavior. Only the distracted driver condition had a small but significant effect.

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[4] This chapter is under review: Núñez Velasco, J.P., Lee, Y.M., Uttley, J., Solernou, A., Farah, H., Van Arem, B., Hagenzieker, M., & Merat., N. (under review). Will Pedestrians Cross the Road before an Automated Vehicle? The Effect of Drivers' Attentiveness and Presence on Pedestrians' Road Crossing Behavior.

5.1 Introduction

Pedestrians are one of the most vulnerable road users in traffic because of their relatively low mass and their lack of a protective shell that can absorb the kinetic energy that is created in a crash with another road user. Accidents between pedestrians and motorized vehicles are the main causes of pedestrians' deaths, globally, with 310,500 killed in 2018 (World Health Organisation, 2018a). Automated vehicles (AVs) are expected to reduce traffic accidents and thus reduce pedestrian fatalities, but that remains to be proven (ITF/OECD, 2018). In particular, highly automated vehicles (i.e. level 4/5; SAE International, 2016) are expected be able to operate without a driver, a human on board, or the driver will be allowed to do other tasks and therefore might appear distracted to other road users. The effect it will have on pedestrians is of importance as to increase safety. AVs should be able to interact with all kinds of road users. Therefore, the interaction between AVs and pedestrians has been recently receiving growing attention.

Studies on pedestrians' road crossing behavior have shown that the speed of the vehicle, its distance to the pedestrian, road infrastructure, and pedestrians' characteristics are determinant factors of pedestrians' road crossing behavior (Rasouli, Kotseruba, & Tsotsos, 2018a). The gap between a pedestrian and a vehicle has been a main focus point in a number of studies. The mean accepted time gap for the pedestrians to cross the road, while interacting with conventional vehicles, has been found to be between 3 to 7 seconds. If the time gap is lower than 3 seconds, it is unlikely for a pedestrian to cross, while the likelihood of crossing increases if the gap is higher than 7 seconds (Rasouli, Kotseruba, & Tsotsos, 2018b). Pedestrians can make a rough estimate of when a vehicle will arrive at their position, but base their crossing decision mainly on the perceived distance (Oxley et al., 2005). The assessment of the distance and speed of the vehicle deteriorates with increasing vehicle speeds (Sun, Zhuang, Wu, Zhao, & Zhang, 2015). Although, there is much evidence suggesting that motion cues and implicit information are the most commonly used to decide crossing, and that explicit communication rarely occur in the current interactions between pedestrian and vehicle (Lee et al., under review; Dey & Terken, 2017) and sometimes the presence of drivers is not even perceived (Risto, Emmenegger, Vickhuyzen, Cefkin & Hollan, 2017, Sucha, Dostal & Risser, 2017; Straub & Schaefer, 2018), the situation might change while interacting with Automated Vehicles.

Studies that have used the "Wizard of Oz" technique (which, for example, involves control by a human hidden behind an especially designed seat) to mimic a driverless AV found no difference in pedestrians' crossing behavior, compared to when the vehicle was driven by a visible human driver (A. Rodríguez Palmeiro et al., 2018; Rothenbücher et al., 2016). However, when asked how the individuals felt while interacting with a driverless vehicle, most reported themselves to have acted differently than normal (A. Rodríguez Palmeiro et al., 2018), or were simply less willing to cross (Lundgren et al., 2017).

The aim of the current study is to investigate the effect of a driver's presence and a driver's perceived attentiveness on pedestrians' crossing behavior. We employed an immersive virtual reality environment that allowed experimental control over the presence and attentiveness of drivers which otherwise will not be allowed in real life unless, until Automated Vehicles demonstrators are ready to be tested. The VR also allowed the time gaps, speed and deceleration to be fully controlled, and the participants'/pedestrians' actual crossing behavior to be measured. Crossing behavior is recorded as well as psychological factors that can shed insights into the mechanisms of why the behavior is performed. We expect that the motion cues are going to have the largest effect on crossing behavior (in line with Oxley et al., 2005; Sun et al., 2015). Our expectations are that psychological factors such as trust and perceived behavioral control could affect pedestrians' crossing behavior. If the findings show that the driver conditions affect the crossing decisions, one could conclude that there may be an added value of external Human Machine Interfaces (eHMIs) in the future AVs. However, if that is not the case there may be a need to rethink the purpose and capabilities of such interfaces. Thus, our findings can help to design AVs in a safe way.

5.2 **Method**

This section will explain the research methodology used in this study.

5.2.1 Participants

Twenty individuals participated in the experiment and they all completed the 108 crossing trials. Eleven out of twenty participants were female, and all were British. They had never suffered from extreme motion sickness and did not have a history of epilepsy. Their age varied from 18 to 33 years old, ($M = 22.8$; $SD = 3.8$). Eighteen of the participants reported in a survey that they knew to some extent what an automated vehicle is, and everyone noticed the differences between the driver conditions and could tell which conditions were presented. Two participants were not able to complete the experiment due to equipment failure and only completed 72 out of 108 trials. No participants fell out due to motion sickness. The experiment was approved by University of Leeds Research Ethics Committee - Ref: LTTRAN-097. All participants received £10 to compensate their time for completing the study.

Table 12. Independent variables included in the scenarios.

Variable name	Levels	Annotation	Explanation
Driver	3	AD	Attentive Driver
		DD	Distracted Driver
		ND	No Driver
Yield	2	Y	The vehicle yielded for the pedestrian
		NY	The vehicle did not yield for the pedestrian
Gap size	2	SG	Gap between vehicle and pedestrian was 3.5 seconds
		LG	Gap between vehicle and pedestrian was 5.5 seconds

5.2.2 Design

The design of this experiment is adapted from Lee, et al. (2019) as is the virtual environment. Participants were asked to cross the road between the two approaching vehicles if they felt safe to do so. In half of the scenarios, both vehicles continued driving with a constant speed of 30 kmph and without yielding to the pedestrian. In the other half, only the second vehicle decelerated and came to a full stop 2.5 m before reaching the pedestrian's crossing path, i.e. yielding to the pedestrian. A 3 x 2 x 2 repeated measures design was used to investigate the crossing behavior in an immersive virtual reality (VR) environment. The three independent variables were: (1) Driver's status: no-driver, attentive driver or distracted driver. (2) The time gap between the first and second vehicles: 3.5 seconds or 5.5 seconds, and (3) the second vehicle's yielding behavior: yielded or not yielded. We choose these crossing gaps because we wanted to gain insights in how the variables affected pedestrians' crossing behavior in a critical and in a less critical scenario. Literature shows that the gap that around 2 seconds is the minimal critical gap (Das, Manski, & Manuszak, 2005) and gaps of 5.3 seconds or more were the most accepted gaps (Brewer, Fitzpatrick, Whitacre, & Lord, 2006). The combination of these factors resulted in 12 conditions, as shown in Table 12. During the scenarios multiple measurements of behavior were made as can be seen in Table 13. These 12 conditions were repeated 3 times per block, and the study consisted of a total of 3 blocks. Thus, each participant faced 108 crossing trials (12 scenarios x 3 repetition per block x 3 blocks). These multiple trials per scenario helps reduce measurement error. The scenarios were randomized in each block to reduce order effects.

Table 13. Dependent variables that formed the crossing behavior.

Variable name	Definition
Crossing decision	The decision to cross the road.
Initiation time	The time it took the participant to start crossing (by tracking the head movement), after the first vehicle passed.
Crossing duration	The time it took the participant to reach the other side of the road from the start of crossing.
Safety margin	The time between the participant reaching the opposite side of the road and the second vehicle passing behind the participant.

5.2.3 Apparatus

Virtual Reality simulation

The immersive virtual environment (figure 10) was built using Unity and was presented to the participants with an HTC Vive head-mounted display. The HTC Vive was tracked by two lighthouse sensors that translated the wearer's position in the real world. The virtual environment resembled a one-way street with a sidewalk on both sides of the road in an urban neighborhood as shown in Figure 10. The street featured houses on both sides of the road, and trees and streetlights on opposite sides of the road. The participants started on the tree side and were only able to start a new trial from the same side to eliminate the roadside as a variable. That meant that they had to cross back if they decided to cross. Two boulders were placed on both sides of the road to indicate the starting position and its opposite if the road was crossed in a straight line.

Two sedan vehicles were presented, where the first vehicle was always white, and the second vehicle was always blue. The windows of the vehicles were removed to stop reflections from preventing the driver to be seen. The drivers in both vehicles were male. The driver of the white vehicle was different from the other two in terms of hair and clothing (see figure 10 and 11). The posture of the driver of the approaching vehicle was adapted to create an "attentive", forward looking driver, and a "distracted" driver, a rightwards looking, driver (see figure 11). The driver was sitting on the right seat of the vehicle behind the wheel as is custom in the UK. The "no driver" condition consisted of a vehicle without anyone inside the vehicle. The vehicle's speed was 30 kmph.

The recorded measurements inside the virtual reality simulation can be found in Table 13. The reference point for the initiation time was set to be the point in time were the first vehicle passed the pedestrian and thus the road was clear for the pedestrian to cross before the arrival of the second vehicle. To measure the initiation time, we used the head movement of the participants to determine the exact moment they initiated their crossing. A down- and forward tilt of the head indicates that the participant is going to start crossing the road (Lee et al., 2019). The initiation time is tightly linked with the gap between the pedestrian and the vehicle. The gap becomes smaller when the initiation time is higher. The crossing duration gives an indication of the walking speed of the pedestrian. The walking speed can be used as a proxy for the safety the pedestrian perceives, a slower speed could suggest lower perceived risk.

Figure 10. The environment of the crossing experiment.

Figure 11. The three driver conditions (from left to right): Attentive driver (driver looking straight ahead), distracted driver (driver looking to the right at his phone), and no-driver.

Surveys

We used an adapted version of the Trust in Automation survey developed by Payre, Cestac and Delhomme (Payre et al., 2016) to capture the trust the participants had in automated vehicles. The participants must score their agreement with 6 statements on a 7-points Likert scale. Statements included are for example: *Globally, I trust the automated vehicle*, and *I trust the automated vehicle to avoid obstacles*.

Furthermore, we measured the perceived behavioral control the participants felt (i.e. the perception of being able to perform a behavior successfully (Ajzen, 1991)) per driver condition after completing the three blocks of the VR sessions. Two items adopted from Zhou, Horrey, and Yu (Zhou, Horrey, & Yu, 2009b) were used for this: '*For me, crossing the road in this way would be...'*, and '*I believe that I have the ability to cross the road in this way...'*. The items were scored on a 7-point bipolar Likert scale explaining how easy and how much the participants agree with the statements, respectively. The mean of the two items was used as the

PBC score. Also, the perceived risk per driver condition was measured on a 7-point scale but this one was inverted. The item was the following: *'Crossing the road in this situation would be...'*.

To capture the performance of the VR environment, the Presence Questionnaire and the Misery Scale (MISC) were employed. The Presence Questionnaire contains 16 items over 4 factors (i.e. involvement, sensory fidelity, adaptation/immersion, & interface quality). Questions haptic or sound fidelity were excluded because they were irrelevant. The MISC was used to assess the simulation sickness symptoms of the participants. The participants were able to score how many symptoms they experienced and how heavily on a score from 0 to 10. The MISC was filled in 4 times per participant as detailed in the next section.

Finally, questions about AVs and their perceptions were included in the survey. Participants had to state how much they knew about AVs, and whether they perceived the vehicles in the experiment as AVs. Also, a control question was included which asked the participants to state which driver conditions they had seen. The three conditions were included as answers and a false answer (i.e. "driver and passenger" condition) was added.

5.2.4 Procedure

The procedure consisted of four parts. During the first part, participants were provided with information about the study and what they were expected to do, and written informed consent was obtained. The MISC was filled in before the start of the VR experiment and served as a baseline.

The second part consisted of the VR experiment. They put the equipment on and while they were in the virtual simulation the experiment leader informed them again about where they had to stand, cross, and which button needed to be pressed to start a trial. The participants started at the edge of the road inside of the virtual environment. They had to press a button on their controller to start each next trial and could only do that if they were on the left side of the road as seen from the approaching vehicle. This meant that after crossing the road they had to walk to the initial position before the next trial could start. Participants completed a small number of practice trials, until they said they were ready to start the experiment. Once the experiment started, they experienced 12 different scenarios (3 effects of driver, 2 time gaps, and 2 deceleration profiles) which were repeated three times in random order. This was called a block and each block lasted approximately 15 minutes. After each block, the participant had a break to counter fatigue effects, depending on the participant's need, and filled in the MISC. In total, there were three blocks.

After the third block was completed, the third part of the study commenced. To assess when and if the driver was visible for the participants and at what distance, a task was completed. Six scenarios were presented, three driver conditions multiplied by two time gaps. The participants pressed a button if and when they saw that there was a driver inside the vehicle. The moment the button was pressed and the distance from the pedestrian to the vehicle were recorded. The amount of errors (e.g. pressing when there is no driver or vice versa) were logged.

Finally, the fourth and final part consisted out of an online survey that included the questionnaires in sub-section 2.2.2. Once finished, they received their compensation. In total, the experiment lasted for one hour.

5.2.5 Analysis

The crossing behavior data was analyzed using mixed effect models (MEMs). These models allowed the use of both continuous and categorical variables as dependent variables. Furthermore, MEMs were able to cope with missing data of some participants without completely removing the participants from the dataset. The MEMs used were binomial logistic regression for the data on crossing decision and linear regression for the other three dependent variables (i.e. initiation time, crossing duration, and safety margin). A random intercept was included in all the models to allow individual differences to be captured. Finally, due to a lack of assumption with respect to the error structure an unstructured covariance matrix was assumed (Singer, 1998).

5.3 Results

First, the descriptive statistics are presented followed by the results of the Perceived behavioral control (PBC) and the results of the Perceived risk (PR). Then, the four models on pedestrians' crossing behavior will be presented. Those results will be divided per dependent variable. In addition, the results of the findings on the visibility of the driver are shown. Finally, the results on the Misery Scale (MISC) and the presence questionnaire are presented. In this study, the level of significance used was $\alpha = .05$.

5.3.1 Automated vehicles?

Twelve out of twenty participants, seven males and five females, felt that they were interacting with AVs and the other eight did not. The mean trust in AVs score was 4.1 (SD = 1.0) on a 7-point Likert scale, the more trust the higher the score. There was no difference in trust scores between males (*M* = 4.3, *SD* = 1.1) and females (*M* = 3.9, *SD* = 1.0), *t*(18) = 0.90, *p* = .38, Cohen's *d* = 0.40. Furthermore, participants who thought the vehicles were AVs had a mean trust score of 4.0 (*SD* = 1.1) while those who did not think the vehicles were AVs had a mean score on trust of 4.3 (*SD* = 1.0). The scores were not significantly different, *t*(18) = -0.63, *p* = .54, Cohen's *d* = 0.29. All the participants noticed all the driver conditions.

5.3.2 Pedestrians' crossing behavior

To investigate the effects of the considered factors on the four dependent variables we estimated a MEM per dependent variable which accounted for the driver condition, time gap, yielding behavior, gender, whether the participant thought the vehicles were automated or not, trust in AVs, the perceived behavioral control per driver, and the perceived risk per driver. Interactions were only included there were they aided the understanding of the effects.

5.3.3 Crossing decision

A binary logistics regression MEM with logit link function was used to study the effects of the considered factors on crossing decision, as presented in Table 14. Only the scenarios where the vehicle did not yield were considered for this model because all the participants crossed the road when the vehicle yielded. They were instructed to cross the road as they would in everyday life. When the vehicle was yielding participants crossed all the time, some did before the vehicle came to a standstill and some when the vehicle was at a full stop. However, this model is only considering the binomial decision whether to cross or not. Therefore, variability in the crossing decision was only found in the scenarios were the vehicle did not yield. The results report that the significant variables that affect the crossing decision are time gap, yielding behavior of the AV, gender, whether a participant thought that the vehicle was an AV or not (i.e. AVs?), and

Perceived behavioral control. The driver condition did not have a significant effect on the decision to cross. Time gap and yielding behavior had a negative effect on the decision to cross. Participants crossed less when the time gap was small and when the vehicle did not yield. Gender had a positive effect, men crossed more as compared to women. If the participant thought the vehicle was an automated vehicle, then she/he crossed more as compared to their peers who did not think that the vehicle was an automated vehicle. Finally, the perceived behavioral control had a positive effect on the crossing decisions. The more successful the participants perceived to be able to cross the road, the more they crossed.

Table 14. Estimation results of the crossing decision model.

Fixed Coefficients		Odds Ratio	95% CI	*t*	*p*
Intercept (mean)		1.73	(2.37, 442.93)	-2.61	.68
Driver (ND, AD[1])		1.24	(0.83, 1.84)	-1.06	.29
Driver (DD, AD[1])		1.54	(0.96, 2.42)	-1.77	.07
Time gap (3.5s, 5.5s[1])		0.08	(0.06, 0.12)	14.30	<.001
Gender (M, F[1])		2.10	(1.42, 2.83)	-3.94	<.001
AVs? (Yes, No[1])		0.58	(0.42, 0.84)	2.95	<.01
Trust in AVs		1.10	(0.94, 1.27)	-1.19	.23
Perceived Behavioral Control		1.19	(1.00, 1.37)	-2.00	.04
Perceived Risk		1.06	(0.91, 1.23)	-0.74	.46
Random Effects		Estimate	S.E.	*Z*	*p*
μ_0	ParticipantID: intercept (var)[2]	1.54			
Model Performance					
-2LL	4281.51				
AIC	4283.51				
BIC	4288.45				

[1]Reference category. [2]Variable was redundant. Participants: 20. Total number of cases: 1043.

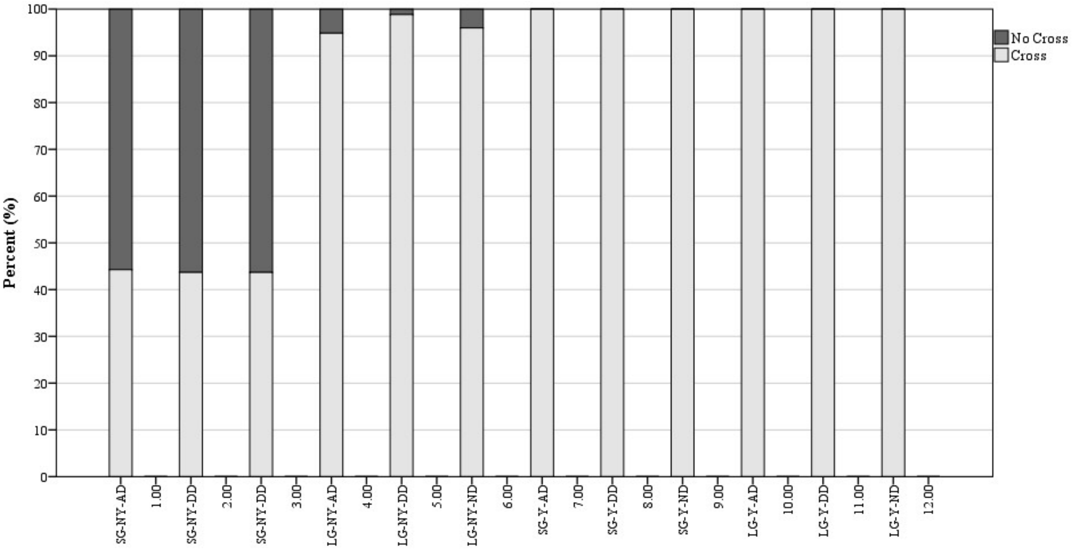

Figure 12. The percentage of crossings per scenario (labels are in Table 1).

5.3.4 Initiation time

A linear regression MEM was used to assess the effects of the factors considered and the interactions between them on the initiation time. The initiation time reference point was the first moment the participant could cross the road after the first vehicle had passed. If participants crossed before that, the initiation time was negative. The initiation time was only recorded if the participant crossed in between vehicles. In figure 13 we can see that if the vehicle is yielding, the mean initiation time is the highest when the time gap is short. In contrast, when the vehicle is not yielding the initiation time is the highest when the time gap is longer which is surprising. This meant that most of the participants decided to cross after the vehicle had stopped completely. Therefore, an interaction effect of time gap and yielding was included in the model. In addition, an interaction effect of yielding behavior and driver condition was included to assess whether an interaction happened. Of the different driver conditions, only the distracted driver differed significantly from the attentive driver condition, as shown in Table 15. So, the initiation time of the participants was longer in the distracted driver condition. In addition, when the vehicle did not yield and there was a distracted driver, the initiation time was significantly shorter as compared to the other scenarios. Time gap was a very strong factor that influenced the initiation time. The initiation time was significantly longer when the time gap was 3.5 seconds compared to 5.5 seconds. This is explained by the interaction between the yielding behavior and time gap. When the time gap was 3.5 seconds and the vehicle did not yield, the initiation time was significantly shorter as compared to the other combinations of time gap and yielding behavior. Yielding behavior of the vehicle did not have a significant effect on the initiation time.

Furthermore, the gender of the participants had a significant effect on the initiation time. Male pedestrians have shorter initiation time compared to female pedestrians. The effect of expecting to be interacting with automated vehicles (i.e. AVs?) had a significant positive effect on the initiation time which means that participants that thought they were interacting with AVs started crossing the road later and thus accepted a smaller gap. In contrast, trust in automated vehicles did not affect the initiation time significantly. The perceived behavioral control per driver condition had a small significant positive effect on the initiation time. Perceived risk had a small significant negative effect.

When only the non-yielding scenarios were considered in the model, we found that the initiation time decreased when the time gap was shorter. This means that participants crossed earlier when they were confronted with a short time gap. Furthermore, we see that the effect of the distracted driver becomes non-significant.

Table 15. Estimation results of the initiation time model.

		All		*Without Yielding*	
Fixed Coefficients		Estimates(S.E.)	*p*	Estimates(S.E.)	*p*
β_0	Intercept (mean)	-0.24 (1.26)	.85	-0.28 (0.18)	.12
β_{Driver}	Driver (ND, AD^1)	-0.04 (0.03)	.15	-0.03 (0.02)	.18
β_{Driver}	Driver (DD, AD^1)	0.07 (0.04)	**.05**	-0.03 (0.02)	.19
$\beta_{gapsize}$	Time gap (3.5s, 5.5s^1)	3.08 (0.13)	**<.001**	-0.09 (0.01)	**<.001**
β_{yield}	Yielding behavior (NY, Y^1)	-0.03 (0.02)	.24	-	**-**
β_{Gender}	Gender (M, F^1)	-0.12 (0.02)	**<.001**	-0.10 (0.02)	**<.001**
β_{AVs}	AVs? (Yes, No^1)	0.24 (0.01)	**<.001**	0.24 (0.02)	**<.001**
β_{Trust}	Trust in AVs	-0.01 (0.01)	.07	-0.01 (0.01)	.27
β_{PBC}	Perceived Behavioral Control	0.04 (0.05)	**<.001**	0.03 (0.01)	**<.001**
β_{PR}	Perceived Risk	-0.02 (0.01)	**.02**	-0.02 (0.01)	.04
$\beta_{Int:Y\&Driver}$	Yielding behavior*Driver (NY*DD)	-0.10 (0.04)	**.01**	-	-
$\beta_{Int:Y\&TimeGap}$	Yielding behavior*Time gap (NY*3.5s)	-3.17 (0.13)	**<.001**	-	-

[1]Reference category. [2]Variable was redundant. Participants: 20. Total number of cases: 1776.

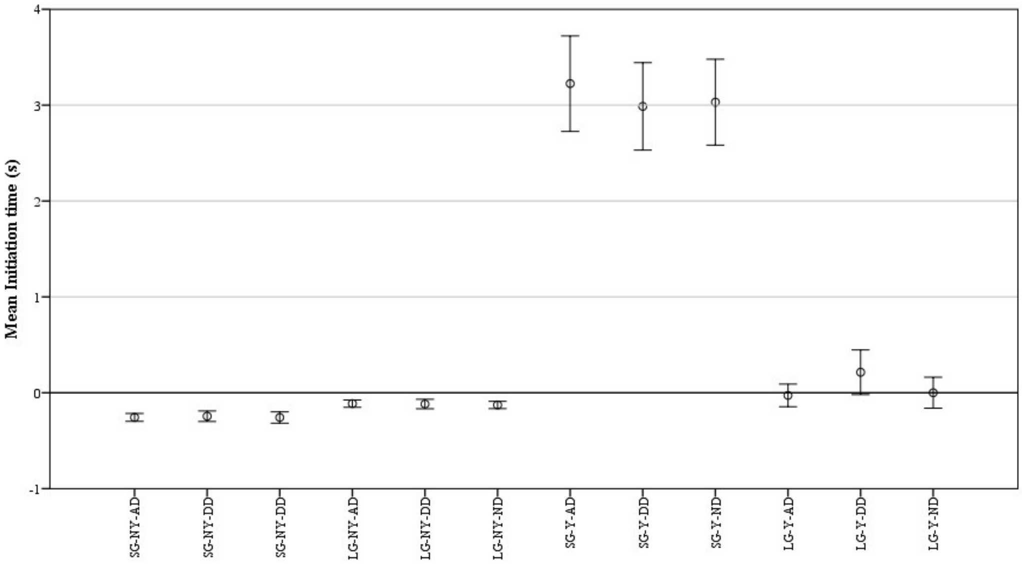

Figure 13. The mean initiation time per scenario (labels are in Table 12).

5.3.5 Crossing duration

The results of the linear regression MEM of crossing duration are presented in Table 16 and figure 14. Driver condition did not have a significant effect on crossing duration. Neither did time gap and vehicles' yielding behavior. Gender did have a significant effect on crossing duration. Males needed less time to reach the other side of the road as compared to females. Perceiving the vehicles as automated also significantly impacted the crossing duration. Those who did not think the vehicles were automated crossed faster than those who did. Finally, perceived behavioral control had a positive effect on the crossing duration. The higher one's perceived ability to successfully cross the road the more time one took to cross the road. Other factors were not found to be significant in this model.

The model reflecting the results of all the non-yielding scenarios shows that the crossing duration became shorter when the time gap was smaller. Perceived Behavioral Control was not found to be significant in this model.

Table 16. Estimation results of the crossing duration model.

		All		*Without Yielding*	
Fixed Coefficients		Estimates (S.E.)	p	Estimates (S.E.)	p
β_0	Intercept (mean)	3.85 (0.53)	**<.001**	3.62 (0.51)	**<.001**
β_{Driver}	Driver (ND, AD[1])	0.00 ()	.99	0.01 (0.04)	.78
β_{Driver}	Driver (DD, AD[1])	0.03 ()	.48	0.01 (0.05)	.89
$\beta_{gapsize}$	Time gap (3.5s, 5.5s[1])	-0.37 ()	**<.001**	-0.66 (0.04)	**<.001**
β_{yield}	Yielding behavior (NY, Y[1])	-0.34 ()	**<.001**	-	-
β_{Gender}	Gender (M, F[1])	-0.25 ()	**<.001**	-0.27 (0.04)	**<.001**
β_{AVs}	AVs? (Yes, No[1])	0.53 ()	**<.001**	0.40 (0.04)	**<.001**
β_{Trust}	Trust in AVs	-0.02 ()	.09	0.02 (0.02)	.16
β_{PBC}	Perceived Behavioral Control	0.07 ()	**<.001**	0.04 (0.02)	.07
β_{PR}	Perceived Risk	-0.01 ()	.97	0.02 (0.02)	.33

[1] Reference category. [2] Variable was redundant. Participants: 20. Total number of cases: 1773.

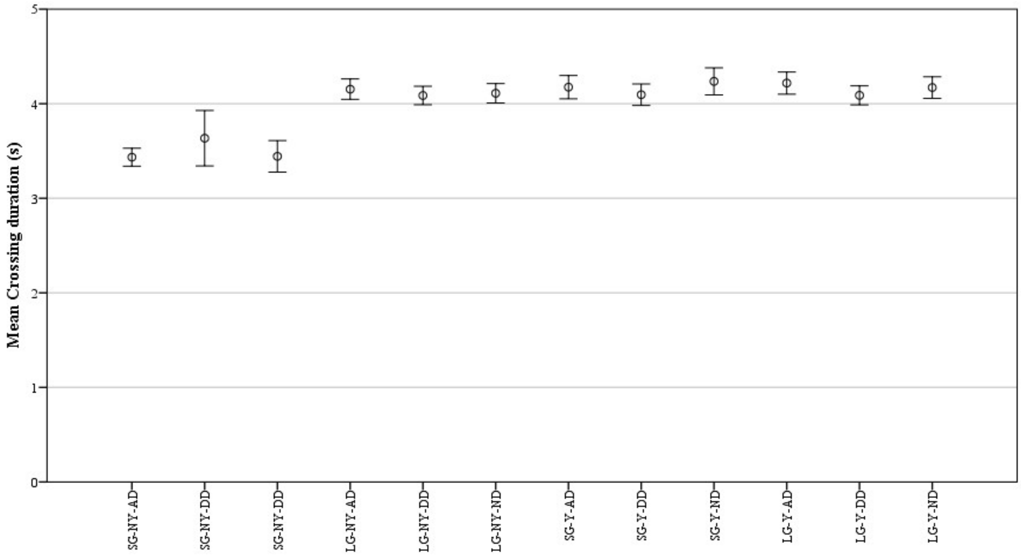

Figure 14. The mean crossing duration per scenario (labels are in Table 12).

5.3.6 Safety margin

Finally, the results on safety margin can be found in Table 17 and figure 15. Driver condition did have a significant effect on safety margin. The 'no driver' nor the 'distracted driver' condition affected safety margin significantly as compared to an attentive driver condition. Also, the vehicles' motion cues, time gap and yielding behavior, did have a significant effect on safety margin. The safety margin was smaller when the time gap was 3.5 seconds as compared to when a 5.5 seconds time gap was used. When the vehicle did not yield the safety margin was significantly smaller as compared to when the vehicle did yield. Furthermore, gender had a significant effect on the safety margin. Males had a significantly larger safety margin as compared to females. Participants who thought that the vehicles were automated had a significantly smaller safety margin as compared to their peers who did not think that. The remaining variables were not found to affect the safety margin significantly.

The model with only non-yielding scenarios shows that the driver condition was not a significant predictor of the safety margin anymore. Furthermore, the effect of the time gap increased as did the effect of suspecting the vehicles being AVs.

Table 17. Estimation results of the safety margin model.

		All		*Without Yielding*	
Fixed Coefficients		Estimates (S.E.)	*p*	Estimates (S.E.)	*p*
β_0	Intercept (mean)	2.33 (0.48)	**<.001**	1.66 (0.55)	**<.01**
β_{Driver}	Driver (ND, AD[1])	-0.08 (0.04)	**.03**	-0.01 (0.08)	.88
β_{Driver}	Driver (DD, AD[1])	-0.06 (0.04)	.11	-0.10 (0.09)	.27
$\beta_{gapsize}$	Time gap (3.5s, 5.5s[1])	-0.66 (0.02)	**<.001**	-1.40 (0.06)	**<.001**
β_{yield}	Yielding behavior (NY, Y[1])	-0.92 (0.03)	**<.001**	-	-
β_{Gender}	Gender (M, F[1])	0.13 (0.03)	**<.001**	0.24 (0.07)	**<.001**
β_{AVs}	AVs? (Yes, No[1])	-0.30 (0.03)	**<.001**	-0.58 (0.07)	**<.001**
β_{Trust}	Trust in AVs	-0.01 (0.01)	.57	0.05 (0.03)	.11
β_{PBC}	Perceived Behavioral Control	-0.04 (0.01)	**.02**	-0.06 (0.03)	**.05**
β_{PR}	Perceived Risk	-0.02 (0.01)	.28	-0.01 (0.03)	.89

[1] Reference category. [2] Variable was redundant. Participants: 20. Total number of cases: 1776.

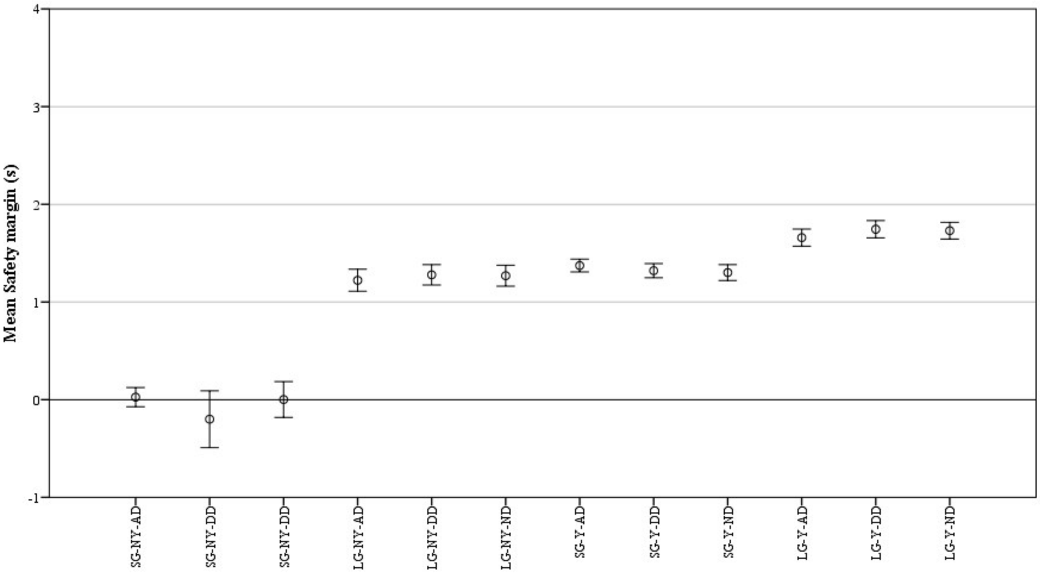

Figure 15. The mean safety margin per scenario (labels are in Table 1).

5.3.7 Perceived Behavioral Control (PBC) & Perceived Risk

After the VR study, participants were asked to complete the perceived behavioral control (PBC) and the perceived risk questionnaires, for each of the three driver conditions. Significant differences were found between the various driver manipulations and the behavioral control the participants perceived, F(2,519) = 9.89, p < .001. The participants' perceived behavioral control was significantly higher with the attentive driver (M = 5.61, SD =1.29) as compared to the inattentive (M = 4.55, SD = 1.40) and no-driver conditions (M = 5.03, SD = 1.44), as a result of a paired comparison test with Bonferroni correction, p < .001. The perceived risk is significantly different between driver manipulations, F(2,519) = 144.92, p < .001. A paired comparison test with Bonferroni correction showed again that perceived risk inverted score was significantly higher with the attentive driver (M = 5.69, SD =1.24) as compared to the inattentive (M = 3.02, SD = 1.60) and no-driver conditions (M = 3.98, SD = 1.57), p < .001 meaning that they felt safer during the attentive driver condition as compared to the other two conditions. No significant differences were found for both PBC and PR between the conditions no-driver and inattentive driver.

5.3.8 Visibility driver

To assess how well the participants were able to see the driver conditions we asked them to report the moment they were able to see the driver. The distance of the vehicle to the participant and the accuracy of the participants were recorded and examined. Fifteen participants did not make any error. Four participants had 1 error out of six trials, and one had 2 errors. The mean distance a participant was able to distinguish a driver sitting inside the vehicle was 34.2 meters (SD = 14.5). The time it took the vehicle to close the mean distance was 4.1 seconds. The distance varied from 10.3 to 75.3 meters. Three errors were false positives (i.e. participants pressed the button when there was no driver) and three were false negatives (i.e. participants failed to press the button when there was a driver). All of the false negatives occurred when there was a distracted driver aboard the vehicle. No significant difference was found in the distance needed to identify a vehicle with a distracted driver (M = 34.4, SD = 13.3) as compared to an attentive driver (M = 34.0, SD = 15.7), t(75) = 0.12, p = .91.

5.3.9 Misery Scale (MISC)

The results of the MISC can be found in Table 18. The participants did not experience simulation sickness during our experiment. The mean score was always below 1. The highest MISC score was "2" which indicates that the participants experienced vague dizziness, warmth, headache, stomach awareness, and/or sweating. None of the participants dropped out because of simulation sickness.

Table 18. The results of the Misery Scale (MISC) per session.

	Baseline	Session 1	Session 2	Session 3	Final
Mean	0	0.60	0.70	0.50	0.37
Std. Deviation	0	0.68	0.66	0.62	0.50

5.3.10 Presence Questionnaire

The Presence questionnaire was used with 16 items on a 7-point scale (1 = low presence, 7 = high presence). The descriptive statistics can be found in Table 19 for 3 factors: involvement, adaptation/immersion, and interface quality. The factor sensory fidelity was removed from the scale because it was irrelevant for this study. The factors "Involvement" and "Adaptation/Immersion" scored high relative to the "Interface quality" factor.

Table 19. Descriptive Statistics of the Presence Scales (Range: 1 (low) to 7 (high).

	Involvement	Adaptation/ Immersion	Interface quality	Total mean
Mean	5.28	5.87	2.58	4.96
Std. Deviation	0.69	0.51	1.06	0.44

5.4 Discussion

The aim of this study was to investigate the effect of driver presence and attentiveness on the crossing behavior of pedestrians. In addition, users' perceived behavioral control and perceived risk were measured per driver condition. Finally, the realism of the virtual reality environment was tested.

5.4.1 Driver condition

Driver condition (attentive, distracted or no driver) was found to influence the time it took participants to start their crossing (i.e. initiation time) but not on the other three measures of behavior. This effect was only significant in the distracted driver condition and was small and positive. The longer crossing initiation time when confronted with a distracted driver implies a smaller gap is accepted, as compared to the attentive driver or absent driver conditions. This result was unexpected, since we assumed that a distracted or absent driver would be perceived as riskier than the attentive driver condition comparable to what was found in the previous literature (Habibovic et al., 2016b). If that were the case, we would have found lower initiation times in the riskier scenarios meaning that the participants accepted only a larger gap in comparison to the attentive driver condition. A bigger gap is safer, namely. It could have been that it took the participants more time to decide whether to cross or not if the driver was distracted. Initiation time is likely to reflect the decision-making process – the longer it takes to decide to cross, the slower the initiation time.

However, the significant effect of distracted driver was not found in the non-yielding scenarios. That could indicate that the pedestrians only hesitated when the vehicle was yielding and was close enough to the pedestrians for the driver to be seen. Only then, the pedestrians might have hesitated due to being confronted with a distracted driver. Therefore, in more ambiguous situations, like the distracted driver (a driver is present, but not clear if he is paying attention), might lead to greater indecision than a more obvious scenario (no driver, attentive driver). Given that in the future, we are probably more likely to see 'distracted driver' on the driver seats than no drivers, then maybe there might be a need to communicate that a vehicle is automated.

5.4.2 Motion cues

The time gap had a large effect on the initiation time. When the time gap was 3.5 seconds, participants crossed later than when it was 5.5 seconds. This is counterintuitive but it can be explained by the interaction time gap has with yielding behavior. The interaction shows that when the time gap is 3.5 seconds and the vehicle did not yield, the initiation time of the participants to cross was significantly shorter as compared to the other scenarios. This result is as expected. Pedestrians will decide sooner whether to cross or not if the time during which they must decide is limited. We did not find an effect of yielding behavior of the vehicle on the initiation time. So, whether the vehicle yields or not did not affect pedestrians' initiation time. The interaction between time gap and yielding behavior is what affected the initiation time. If the vehicle was far away, it did not matter whether it was yielding because participants were already willing to cross. The opposite was also true. If the vehicle was close, participants preferred to wait till it was almost standing still before they crossed. So, motion cues had the biggest impact on the time it took the pedestrians to initiate a crossing. This is in congruence with previous studies (Mahadevan, Somanath, & Sharlin, 2018; Rothenbücher et al., 2016). Safety margin was also affected by time gap and yielding behavior of the vehicle. The safety margin was lower when the time gap was smaller. In that case, there was less time to cross the road which lead to the vehicle being closer to the participants when they reached the opposite site. Furthermore, when the vehicle did not yield the time was limited. Overall, the time gap and yielding behavior were significant predictors of initiation gap and safety margin.

Participants' crossing decision was significantly affected by the vehicles' motion cues. However, the design of the experiment forced the participants to cross when the vehicle yielded. So, the yielding behavior was a less important factor when examining the crossing decisions even though it had one of the largest effects. Time gap had a large effect on crossing decision. The participants crossed less when the time gap was smaller. This was as expected. Crossing duration was also found to be significantly affected by vehicles' motion cues. This could mean that if the crossing could not be made within a certain time frame participant decided not to cross the road.

5.4.3 Perceived behavioral control & Perceived risk

As expected, the score on perceived behavioral control when interacting with a present and attentive driver was higher than when compared with the other two conditions. So, the participants felt they were most likely to cross successfully when the driver was attentive. In addition, the inverted scores on perceived risk when the driver was present and attentive were higher than in the other conditions. In other words, the participants perceived more risk when interacting with a distracted or non-present driver as compared to an attentive one. However, only the distracted driver condition lead to a small significant effect on crossing behavior. The participants needed more time to decide whether to initiate the cross. The explanation could be that a distracted driver is perceived riskier because it is unclear whether the vehicle is operating in automated mode. In contrast, when no driver is presented, the vehicle operating automatically seems more likely. Nevertheless, the effects on crossing behavior were small compared to other factors such as time gap.

5.4.4 Visibility

Overall, the participants needed between 75.3 and 10.3 meters of distance from them to the vehicle to be able to distinguish the driver. On average, 34.2 meters was enough to tell whether there was a driver present. This meant that the participants saw the driver on average 4.1 seconds before the vehicle arrived next to the participant because the vehicle was travelling at 30 kmph. So, the driver was most probably visible to the participant before they could cross when the time gap was 3.5 seconds. On the other hand, the driver was visible on average 1.5 seconds after the participant was able to cross when the time gap was 5.5 seconds. In other words, the vehicle was further away than 34.2 meters when participants started to cross. This means that the driver condition would have a major effect on the shorter time gap because it was better distinguishable, but this was not supported by the data. No interaction effect between driver condition and time gap was found. Thus, the effect of being able to spot the driver did not influence the initiation time. This suggests being able to see a driver is irrelevant when deciding to cross when there is a reasonably safe time gap between vehicles. Only six errors were made out of 120 trials which indicates that the participants were fairly good at identifying whether there was a driver present at some point. It must be considered that the virtual windows of the vehicle were removed, and that the low speed of the vehicle was in place to make sure the driver would be visible. Even with the adaptations we made, the vehicle needed to be relatively close to the pedestrian. Furthermore, the test took place in a virtual world which means that the findings cannot be directly translated to the real world. However, it does raise questions about the utility of eye contact. Although, some papers seem to hint that eye contact is used by pedestrians to decide whether to cross (e.g. Rasouli & Tsotsos, 2019), it seems that eye contact cannot be used in all situations. Still, interactions occur without the possibility of seeing the other road users' eyes leaving unclear the importance of eye contact. Our findings show that there is a limited range in which the driver can be distinguished, and it is to be expected that the vehicle needs to be even closer for a pedestrian to be able to see the drivers' eyes. In addition, the vehicles' behavior was a better predictor of the crossing behavior meaning that the importance of the driver may be overestimated. Further, this leads to questions about the usability and relevance of electronic Human-Machine interfaces (eHMIs) as the readability of these interfaces will depend on factors such as the speed of the vehicle and distance to the pedestrian, lighting conditions, and objects blocking the view. Our results suggest pedestrians may make decisions to cross or not when the vehicle is at a distance that may make the use of an eHMI irrelevant. Future research should focus on the range of usability, added value of eHMIs and for what kind of maneuvers (of both vehicles and pedestrians) eHMIs should be used.

5.4.5 Virtual Reality performance

In terms of realism, the scores on the presence scale are good overall, except on the interface quality. The scores on the misery scale were good and showed that the participants experienced vague symptoms of simulation sickness at most. Mostly, no symptoms were experienced. This is to be expected according to previous studies (Núñez Velasco, Farah, van Arem, & Hagenzieker, 2019; Schwebel, Severson, & He, 2017). The use of this type of virtual reality proved to be useful for this kind of studies.

5.4.6 Limitations

This study was performed in a virtual reality environment which means that the results are not directly generalizable to the real world. However, studies suggest that the trends in virtual reality correlate with real world effects (Schneider & Bengler, 2020). More research is needed to prove the generalizability of findings from virtual reality studies. The visibility within the virtual environment may not be the same as in the real world. Furthermore, the windows were removed from the vehicles to increase visibility. Field experiments may find that the glare of windows or other factors introduced by glass windows may affect driver visibility.

The sample size was small and homogenous, and therefore further research should focus on the differences in crossing behavior when interacting with AVs between cultures, gender and age.

The task designed to test how well the driver was visible was performed at the end of the virtual reality session leaving unclear at what moment the participants started to notice the various driver conditions. This was done on purpose to not influence the crossing decision tactics of the participants.

5.5 Conclusions

This VR study illustrated that the most important factor affecting pedestrians' road crossing behavior was the motion cues derived from the vehicle, rather than the presence or state of the driver. This raises the question about the needs, purpose, and added value of eHMIs. Immersive virtual reality is a useful tool to study the mechanisms of pedestrians' crossing behavior.

Chapter 6 - Discussion & Conclusion

In this dissertation I studied the effects of automated vehicles (AVs) on vulnerable road users (VRUs) crossing intentions and behavior. The main objectives were to provide insights into the interactions between AVs and VRUs and the underlying mechanisms of these interactions; to study the road crossing intentions of pedestrians and cyclists; and to investigate the road crossing behavior of pedestrians. Therefore the goal of answering the proposed research questions below was pursued:

To what extent do AVs affect the crossing behavior of pedestrians and cyclists?

1. What are the underlying factors that determine vulnerable road users' crossing behavior when interacting with an AV and how could AVs affect these factors and VRUs crossing behavior?
2. How do the physical appearance and external human-machine interfaces (eHMI) of an AV affect pedestrians' crossing intentions in comparison to vehicles' motion cues and psychological factors?
3. How does the physical appearance of an AV affect cyclists' crossing intentions in comparison to vehicles' motion cues and psychological factors?
4. How does the presence and attentiveness of drivers in an AV affect pedestrians' crossing behavior in comparison to vehicles' motion cues and psychological factors?
5. How does Virtual Reality perform as a research method in terms of realism, validity and ease of use??

In this chapter the main conclusions of the dissertation are presented and discussed. First, the main findings will be presented. Then, the implications of the research findings for science and practice are discussed. Finally, the recommendations for future research are given.

6.1 Main Findings & Discussion

The AVs, VRUs and infrastructure are the three main components that were identified based on the literature which could influence the interactions between AVs and VRUs and therefore are included in the developed theoretical framework (figure 16). The most important factors belonging to the identified components when studying vulnerable road users' crossing behavior consist of psychological factors, vehicle automation and factors, and road design. The selected psychological factors considered were trust in automated vehicles, perceived behavioral control, and crossing intentions. The selected vehicle factors were the speed of the vehicle, distance of the vehicle to the vulnerable road users and yielding behavior. The automation factors were AVs' physical appearance, presence and attentiveness of a driver, and the presence of eHMIs. The main conclusions of this dissertation are the following.

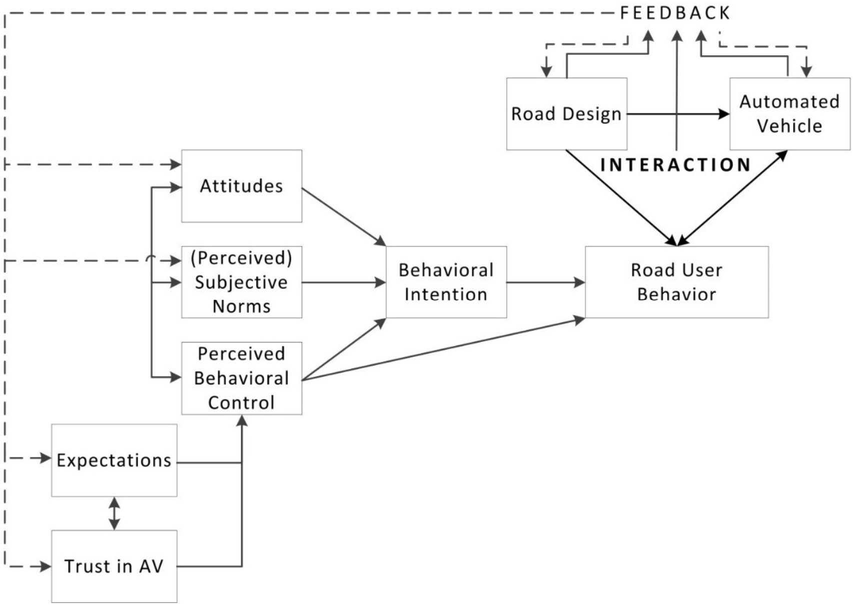

Figure 16. The theoretical framework as proposed in Chapter 2

6.1.1 Automation factors

To study the effects of AVs on VRUs behavior, a subset of characteristics was chosen. The choice of this subset of characteristics was based on the characteristics that were expected to be different when comparing AVs to conventional vehicles (CVs) and based on the literature review which indicated that these characteristics could influence the behavior of VRUs. These selected AV's characteristics are: the AV physical appearance, driver's presence and attentiveness, and the presence of eHMIs.

AVs' physical appearance proved not to affect the pedestrians' and cyclists' crossing intentions. In chapter 3, a futuristic shuttle bus and a CV were used. The appearance of those vehicles did not affect the pedestrians' intentions, even when accounting for the difference in the size between vehicles (*Chapter 3*). It was possible to study the effect of vehicle size by comparing the effect of the vehicles on the intentions of pedestrians who did not recognize the vehicle was an AV with those that did recognize that the vehicle was automated. That allowed us to understand how the physical appearance (i.e. the size of the vehicle) affected pedestrians' intentions to cross irrespective of the automation. In *Chapter 4*, two passenger cars were compared. One of the vehicles was an AV with sensors on the roof, while the other was a CV (a Waymo Ford Chrysler). Cyclists' intention to cross did not differ between these two scenarios. So, neither pedestrians nor cyclist' crossing intentions were affected by the physical appearance of the vehicle. This is in line with most literature (Rodríguez Palmeiro et al., 2018; Rothenbücher, Li, Sirkin, Mok, & Ju, 2016). Some studies did find an effect but these effects were rather small or depending on specific situations, such as the distance of the pedestrian to the vehicle (Dey, Martens, Eggen, & Terken, 2019; Vlakveld, Van der Kint, & Hagenzieker, 2020). Thus, I conclude that the appearance is not an important factor when it comes to interactions between AVs and VRUs at urban intersections.

The **presence of a driver** did not affect pedestrians crossing behavior as was shown in *Chapter 5*. In contrast, a significant effect was found of **drivers' attentiveness** on pedestrians crossing behavior. A distracted driver caused the participating pedestrians to cross the road later as compared to an attentive driver. It should be taken into account that the effects found in this study were significant but small. However, more studies seem to point towards an effect of drivers' presence and attentiveness towards pedestrians' crossing intentions (Lagström & Lundgren, 2015) and time needed to decide to cross (Mahadevan, Sanoubari, Somanath, Young, & Sharlin, 2019). This could have implications for the design of AVs' physical appearance. There might be a need for AVs to be recognizable to decrease confusion of the interacting road users when they approach a vehicle with a distracted driver. Studies that did not find any effect are also found in the literature (Rodríguez Palmeiro et al., 2018; Rothenbücher et al., 2016). As there is no consensus found in the literature, conclusions on the basis of the results of this study should be taken with care. However, the driver's condition is not always perceived due to, for example, lighting conditions or distance (Risto, Emmenegger, Vinkhuyzen, Cefkin, & Hollan, 2017; Sucha, Dostal, & Risser, 2017). I do not expect the driver's condition to affect VRUs when for example the gap between the vehicle and VRU is large enough for the VRU to cross the road without the vehicle getting dangerously close or when the driver condition is not visible due to glare or nightfall. So, the effect on VRUs is dependent on the situation.

Finally, the effects of **eHMIs** on pedestrians' crossing intentions were studied. eHMIs clearly affected the crossing intentions of pedestrians (*Chapter 3*). Participants who were not informed about the objective of the eHMI still reacted to them adequately (i.e. they crossed more when the eHMIs portrayed a green sign with a walking pedestrian and crossed less when the sign portrayed a pedestrian standing still on a red stop sign). This is in line with the literature on eHMIs. However the added value of eHMIs still needs to be proven. This is since eHMIs have been proposed and tested in studies investigating one-on-one interactions between AVs and VRUs. No research has been performed beyond one-on-one interactions. So, it remains unknown whether eHMIs will really improve the interactions of AVs with multiple VRUs. Furthermore, factors such as visibility, VRU type (i.e. cyclist or pedestrian), maneuver of the AV and VRU, and amount of VRUs in the vicinity of the AV could reduce the usability of eHMIs. Thus, eHMIs affected the crossing intentions of pedestrians but more research is needed to understand how eHMIs could be used optimally.

To summarize, the AVs' characteristics were not the most important factors affecting VRUs' road crossing intentions and behavior in the short term. These factors proved to have no or limited effects, except for eHMIs. eHMIs had a clear effect on the crossing intentions of pedestrians.

6.1.2 Vehicles' motion cues

The vehicles' motion cues (i.e. the vehicle speed, its gap to the other road user, and the yielding behavior) were found to be the most important factors affecting the crossing intentions and behavior of pedestrians and cyclists.

Out of the three motion cues included, the distance gap between the vehicle and the other road user was found to be the strongest predictor of crossing intentions and behavior, even stronger than the gap measured in seconds as it removed the vehicle speed out of the equation, in line with Oxley, et al. (2005). Also, earlier studies showed that VRUs have difficulties with making correct speed estimations (e.g. Sun, Zhuang, Wu, Zhao, & Zhang, 2015). The shorter the distance gap the less participants crossed or intended to cross. Similar findings were found in the literature on pedestrians crossing behavior (e.g. Amini, Katrakazas, & Antoniou, 2019; Lee et al., 2019; Oxley et al., 2005; Rasouli, Kotseruba, & Tsotsos, 2018).

Speed of the vehicle was found to be a significant factor affecting the crossing intentions. At first a counter intuitive result was found. The higher the speed, the more pedestrians intended to cross the road. However, this effect was negated when the time gap was transformed into a distance gap. Once the distance gap was included in the model, no significant effect was found of the speed on the crossing intentions of pedestrians. In the literature, studies report speed being one of the most important factors that are considered by VRUs (e.g. Pawar & Patil, 2015) but also that VRUs may not be able to estimate the speed of vehicles correctly (Sun et al., 2015). The speed in itself is not a significant factor, but whether the speed is adapted (i.e. acceleration and deceleration) could be as can be seen in the next paragraph. So, I conclude that speed itself does not have an effect on the pedestrians' crossing intentions.

Yielding behavior of the vehicle was found to be a significant factor affecting the crossing behavior of pedestrians. If the speed was maintained, pedestrians crossed less compared to when the vehicle yielded. Yielding behavior leads the pedestrians to cross more frequently and take more time to cross the road. The yielding behavior affected the timing of the crossing decision only when the gap size was small. So, this confirms the hypothesis that the speed profile (i.e. the acceleration and deceleration of a vehicle over a given distance) is a factor that affects VRUs' behavior. In this case, only the deceleration was studied and it can be concluded that it affects the VRUs' road crossing behavior.

All in all, motion cues were found to have a stronger effect on crossing behavior compared to AV's characteristics. VRUs are able to make crossing decisions based on the motion cues of the vehicle possibly due to their prelearned road crossing strategies (Clamann, Aubert, & Cummings, 2017).
Once the AVs'motion cues differ from the expected behavior, adaptive behavior of VRUs could be expected. For example, once the vehicle behaved different than expected (e.g. approaching a zebra crossing at high speed and braking in the last moment), pedestrians were not able to cross the road (Rothenbücher et al., 2016). Therefore, the behavior of the AV should be considered when studying the interactions between AVs and VRUs.

6.1.3 Psychological factors

To understand the crossing behavior of VRUs, psychological constructs were included in addition to vehicle automation and vehicle factors. These psychological factors helped to provide insights into the underlying mechanisms of crossing intentions and behaviors of VRUs.

Perceived behavioral control (PBC) had a strong relation with crossing intentions (*Chapter 3*). The higher the perceived ability to cross the road, the higher the intentions to cross, which is in line with the Theory of Planned Behavior (TPB; Ajzen, 1991). To further understand what the role was of the vehicle on the crossing intentions, the PBC per physical appearance was measured. It was found that the PBC did not differ per vehicle's physical appearance for pedestrians nor for cyclists. Thus, the physical appearance of the vehicles did not have an effect on PBC (*Chapters 3 & 4*). This coincides with the absence of an effect of the physical appearance on pedestrians' and cyclists' crossing intentions. The driver's presence and attentiveness did have an effect on PBC. An attentive driver resulted in higher PBC than an inattentive or non-present driver. Interestingly, the only driver condition to affect crossing behavior was the inattentive driver condition in contrast to what one would expect based on the findings of PBC. The difference between the PBC found for the inattentive driver and no-driver condition was small but not statistically significant. Furthermore, PBC affected the crossing intentions of cyclists (Chapter 4) as well, in line with TPB. So, in agreement with the proposed theoretical framework and TPB, a relation between PBC and VRUs' crossing intentions and behavior was found. Furthermore, a relation was found between the effects AVs' characteristics had on PBC and on VRUs' crossing intentions and behavior. This is in agreement with my hypothesis stating that expected AVs' characteristics would have a relation with VRUs' PBC and therefore with VRUs' behavior, which is in accordance with TPB.

Trust in automation was another psychological construct that was part of the theoretical framework. I found that the trust in AVs did differ but only between pedestrians who recognized the AV as an AV and those who did not. A difference was found in the crossing intentions between those two groups. In chapter 4, cyclists additionally were asked whether they trusted AVs more, equally, or less than CVs. Only a difference in trust was found between those that trusted AVs less compared to CVs and the other two groups (trust AVs equally and trust AVs more). In addition, cyclists that reported to have more trust showed indications of feeling safer by deciding to not adapt their crossing speed. However, no significant effect of trust was found on crossing behavior. Furthermore, the trust measured in the used questionnaire in this study may refer to the trust participants have in future AVs instead of trust in the AV they were confronted with. This was in agreement with the findings in chapter 4 it was found that dividing the participants in categories depending on whether they trusted AVs more, equally, or less than CVs proved to be a stronger predictor of crossing intentions. Nevertheless, mixed results of trust in AVs were found on crossing intentions of VRUs and none between trust in AVs and crossing behavior. The effects of trust on crossing intentions did not match the effects of physical appearance on the intentions. That is, even though some expressed to trust AVs they did not cross more in front of AVs. Trust may have been oversimplified in the proposed theoretical framework and in the studies conducted in this research. Lee and See (2004) argue that trust is a complex construct that affects and is affected by many factors that were not considered in my studies, such as predisposition to trust, cultural differences, and workload. A relative value of trust in AVs as compared to trust in CVs as in chapter 4 would have fitted the needs of my studies better than an absolute measure of trust in AVs. In this study, the relationship between PBC and trust was not assessed as proposed in the theoretical framework but the relationship of trust on crossing intentions and behavior. Future research could investigate the relationship of trust with PBC and how crossing behavior is affected by trust.

To conclude, a strong positive relation between PBC and crossing intentions and behavior was found as well as with a subset of AVs' characteristics. This is in line with the Theory of Planned Behavior (Ajzen, 1985) as well as the proposed theoretical framework. A relation between relative measure of trust in AVs as compared to CVs and crossing intentions was found. More trust in AVs led to less adaptation of one's intentions when confronted with AVs. In contrast, no relation was found between an absolute measure of trust in AVs and crossing intention. Finally, no relation was found between trust in AVs and crossing behavior.

6.1.4 Road design

Road design was considered in the proposed theoretical framework as one of the main factors influencing road crossing behavior when a VRU interacts with an AV. Threrefore, road design was included as a variable in the presented experiments.

In *Chapter 3* road design was included in the form of the presence of a zebra crossing. The results show that the presence of a zebra crossing increased the pedestrian's intention to cross in comparison with a scenario without zebra crossing. In *Chapter 4*, when cyclists had the right of way, they preferred to continue cycling instead of adapting their cycling speed. So, the VRUs relied on the rules of the road design in their crossing decisions. This suggests that they felt safer when they had the right of way. This is in agreement with literature on road crossing behavior of VRUs where dedicated crossing facilities are present. The studies show that VRUs do not adapt their crossing speed when crossing on a dedicated crossing facility indicating that they feel safe and see no need to cross faster (Crompton, 1979; Tian et al., 2013). The presence of dedicated crossing facilities increases VRUs perceived safety and increases their confidence while crossing the road (Willis, Gjersoe, Havard, Kerridge, & Kukla, 2004).

6.1.5 Theoretical framework

The theoretical framework shows the hypothesized most important factors affecting crossing behavior. The focus was the psychological factors, automation characteristics, vehicle characteristics, road design and on the interaction. Not all the interactions between factors were investigated in the presented studies and therefore I cannot conclude on the full validity of the theoretical framework. However, I did include many factors in the research and studied their effects on the crossing behavior. It was found that PBC influenced the crossing intention as expected from the Theory of Planned Behavior (Ajzen, 1985). The effect AVs' characteristics had on PBC was similar to the effect the characteristics had on crossing intentions and behavior. It was found that the within the interaction, both the vehicle and the road design affected crossing intentions and behavior. The theoretical framework may profit from inclusion of psychological constructs that were considered in my studies but were not included in the theoretical framework, such as perceived risk, familiarity with AVs, and knowledge about AVs.

Frameworks proposed in the literature for researching the decision making process and the interaction of pedestrians with AVs show similarities with the theoretical framework used in this thesis. Rasouli & Tsotos (2019) developed a model aimed at understanding pedestrian behavior and identifying factors that could affect pedestrians' crossing behavior when interacting with AVs. In agreement with the proposed theoretical framework, Rasouli & Tsotos considered factors that belonged to the (automated) vehicle, VRU or the infrastructure and therefore an overlap between the factors they identified and the factors proposed in the proposed theoretical framework was found. For example, vehicle appearance, communication, gap size, vehicle speed, and perceived risk were factors included in both studies. Similar to Rasouli & Tsotos (2019), Amini et al (2019) researched the development of the interaction between road users and identified the main factors of such an interaction. This interaction could be between a pedestrian and a vehicle, and between two vehicles. Their focus was on explaining how the interaction develops and which factors affect these interactions. The factors included in Amini's et. al. framework are in agreement with the ones proposed in this dissertation and Rasouli's &

Tsotos' framework. Future work should focus on validating the theoretical framework and researching the relations between factors in more detail.

6.1.6 Virtual Reality

This dissertation used 360° videos and immersive virtual reality technologies, and questionnaires to study the road crossing intentions and behavior of pedestrians and cyclists when interacting with AVs. Both virtual reality (VR) methodologies 360° has their advantages and disadvantages. The advantages of the developed 360° videos VR compared to immersive VR is that it is easier to set up nad therefore, is also cheaper. The use of video material increases the realism of the VR. However, the fact that the user cannot perform the behavior but only show their intentions is a disadvantage. Therefore, 360° videos VR may not be suitable for all kinds of research. The cameras used showed limitations in terms of resolution and quality of the video recordings limiting the kind of situations that could be used for my studies. For example, high speeds could not be reproduced as the vehicle would have to start at a large distance of the camera and would therefore not be visible in the video. Although, 360° videos VR was new and experimental, my research showed that the performance of 360° videos VR was comparable to immersive virtual reality in terms of realism and usability. Immersive VR does not make use of recordings out of the real world but it lets you measure behavior in a way 360° videos VR cannot. Both VR did make use of a head-mounted display (HMD). The constraint encountered with the HMD is that the field of view gets noticeably limited. The use of peripheral vision is blocked and affected the participants behavior during the practice rounds. It is thus important to let users get used to the equipment to make sure they are able to cope. Furthermore, it was found that participants benefitted from breaks in between testing rounds. This helped them to concentrate again and again and reduced the side effects of VR, such as tiredness or simulation sickness. So, the use of VR was successful and the type of VR which one should use depends on the factors of interest.

The validity and usability of VR is a relatively a new research topic. A recent literature review has shown that the findings of VR studies are partially transferable to the real world (Schneider & Bengler, 2020). For now, it seems that the trends found in VR are the same one would found in the real world (Schneider & Bengler, 2020). A direct comparison between the presented VR types and a field experiment on pedestrian crossing behavior showed that there are indeed differences between VR and field experiment but that they are not significant (Agarwal, 2019). Further research is needed to define the transferability of VR findings to real world effects. The findings in this dissertation are in line with the findings reported in previous literature on pedestrians' crossing behavior. Therefore, the findings of this research are of relevance for the real world. However, the findings are not to be translated directly to the real world but the trends I found may be.

6.2 Conclusion

The main research question was the following: To what extent do AVs affect the crossing behavior of pedestrians and cyclists? To answer the question I investigated which factors should be included when studying the interactions. I found factors pertaining to each of the three components (i.e. AVs, VRUs, & infrastructure), that together form the interacton, are relevant. The presented findings show that AVs will probably not have an effect on VRUs' road crossing behavior in the short term. However, this depends on whether AVs will behave in-line with the VRUs' expectations and if the results from the VR studies can be generalized to real world situations (see next section).. Psychologically, AVs affected the VRUs but it did not result in adapted behavior. The psychological constructs affected were perceived behavioral control, trust in AVs, perceived risk, and familiarity with AVs. I want to emphasize that the results of this study showed that the vehicle factors, in particular the distance gap size, was the most important factor affecting the VRUs' crossing intentions in the short term.

The developed theoretical framework proved useful to gain insights into how the behavior of VRUs could be affected by AVs. The factors included are in agreement with literature on the interactions between vehicles and VRUs. Additional work is needed to validate this theoretical framework, however. The types of VR employed during the presented experiments performed adequately and shows that this type of methodology is helpful to find relevant factors and trends that could also be found in the real world. However, more research on the transferability of results is needed (see next section).

6.3 Limitations

The findings in this dissertation are subject to certain limitations. The participant samples in my studies were homogenous. The samples consisted of young, highly educated, individuals. That means that generalization to other populations should be done with care.

VR methods were used in all the experiments. The added value of VR is its controllability. Every part of the scenario could be adapted to once's wishes but this comes at a cost of realism and complexity. Participants are aware that they are being monitored and tested and might adapt their behavior. Although, literature is increasingly accepting and proving the validity of the results of VR experiments, still more work needs to be performed since the participants do not experience real risk. Furthermore, the amount of variables and actors that can be included in a VR scenario is limited. Few studies focus on studying behavior of several actors inside one VR environment (e.g. Jiang et al., 2018) but more research is needed. Finally, the performance of the VR methods in each study was tested to understand how VR performed. Generalizing to all the possible physical appearances and vehicles speeds is out of order considering the limited variation of variables included in the presented experiments such as speed and physical appearance.

The findings presented are short term effects as many of the participating individuals did not interact with an automated vehicle before my studies. The presented experiments may be the first time these individuals were exposed to automated vehicles. Thus, the results show how vulnerable road users would interact with automated vehicles in the initial phase of automated vehicles being on the road. These participants could once again change their behavior after extensive exposure to automated vehicles. VRUs could learn to behave differently around AVs for different purposes. For example, it could be that VRUs would prefer to increase their safety, and thus behave more cautiously when interacting with AVs. Or the opposite could happen due to a safer feeling when interacting with AVs.

6.4 Implications of findings

The presented findings will have some implications for scientific research and practice. The possible implications are discussed in the following sections.

6.4.1 Recommendations for scientific research

Future research is needed to increase our understanding of the interactions between AVs and VRUs. This research focused primarily on young and highly educated individuals living in western Europe. Future research could investigate the effects of age, educational level, and cultural differences on the interactions between AVs and VRUs. Furthermore, my studies focused on crossing intentions and crossing behaviors exclusively. Thus, effects on interactions that have to do with other behaviors, such as overtakings are not considered. Future studies could focus on a wider variety of behavior and how they are affected by AVs. In addition, in this dissertation I focused solely on one on one interactions but in reality scenarios where more than two road users interact with each other are also common. Therefore, studies should map the most important possibilities of interactions and research how AVs affect these interactions. For example, Markkula et al (2020) created a taxonomy of various road user behavior. This taxonomy can be combined with a map of possible manoeuvres (e.g. overtaking, bypassing, etc.) of road users and various road designs (e.g. roundabouts, intersection, crossing facilities, etc.) to create a framework of which behavior can be expected depending on the road design. This framework could help focus research on VRUs behavior when interacting with AVs. Further, the penetration rate can be expected to affect the interactions between AVs and VRUs. The exposure of VRUs to AVs is expected to increase when the penetration levels of AVs increase. However, it is unclear what the effects of more exposure are on VRUs behavior. Future research should investigate this further.

More research is needed to identify how AVs will behave and how this could affect the behavior of VRUs. As seen in this dissertation, the motion cues appear to be the most important factors affecting VRUs crossing behavior. But, since AVs are controlled by algorithms instead of humans their behavior could be new. Their new motion cues could create a mismatch between the expected motion cues of vehicles and their meaning to VRUs. Therefore, future work should assess how behavior of AVs could be and how it will impact VRUs. It is possible that no typical behavior of AVs can be identified in the near future. Then, I would advise to consider how small changes to AVs behavior could affect VRUs.

eHMIs seem promising when it comes to a one on one interaction between AV and VRU but questions remain to be answered for multiple interactions. In addition, it is unclear whether one type of eHMI could be used for different types of VRUs and for different maneuvers. When to use eHMIs in terms of timing, and maneuver type are also questions that remain unanswered. Future work should try to focus more on answering the question when eHMIs should be used and when it should not (see., e.g. Dey, Matviienko, Berger, Pfleging, Martens, & Terken, 2020; Eisma, Reiff, Kooijman, Dodou, de Winter, 2020; Kaleefathullah, et al., 2020).

In addition, the studies in this research were performed in VR environments. Therefore, field experiments and observational studies should be developed to study the interactions of VRUs and AVs in real life. These studies could validate my results and create insights on how the observed behavior in VR and real life differ. These insights could be used to design more realistic VR environments and scenarios.

Finally, more research is needed to study the effects of AVs on human factors, such as trust, perceived risk, and crossing behavior. Despite an increase of interest for the field more work needs to be done to ensure AVs can drive on the roads and interact safely with human road users. In particular, studies on the interactions of cyclists and AVs are few and more research needs to be done to understand how pedestrians cyclists, and other non-automated road users will be affected by AVs.

6.4.2 Implications for practice

The research was performed in a controlled setting and the scenarios included were limited. This results in a limited transferability of my results for practice. However, some implications for practice can be mentioned.

Municipalities should be encouraged to implement pilots which contain AVs and also include focus on studying the interactions between VRUs and AVs. More care should be dedicated into the behavior of the vehicle. The behavior should match the expectations of VRUs so that the VRUs can interact with them safely. Pilots should not aim to exist for the short term exclusively but, long term pilots should be considered to assess possible behavioral adaptation of VRUs. These pilots would be of most benefit to the municipalities when conducted as a collaboration with both knowledge institutes and the industry developing these AVs.

External human machine interfaces should be used with care. The results show that the use and need of these kinds of interfaces may be limited. Vehicle manufacturers should consider the intended use of the vehicle before making large scale use of specific eHMIs. It is recommended to also develop specific vehicles’ motion cues which make the intentions of the vehicle clear. The behavior should match the intentions of vehicles as to increase the chance that VRUs can predict their intentions. Also, infrastructural adaptations may be of more use than adaptations to the vehicle when it comes to the interaction. My studies show that the use of existing priority regulations helped VRUs to decide whether they should cross or give way, and the literature also shows that one feels more confident and safe when crossing facilities are present. Therefore, these types of road design should not be neglected or omitted in future plans for urban areas.

Finally, information and education towards VRUs should not only focus on the capabilities of AVs but also on the limitations. Teaching road users what they should expect of AVs will help match the expectations road users have of AVs and AVs’ real capabilities. This could result in less confusion and therefore safer and more efficient interactions.

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About the author

Juan Pablo Núñez Velasco was born on March, 21st 1992 in Mexico. He, his parents and his five brothers and sisters moved to the Netherlands in 2000. After finishing high school at Christelijk Gymnasium Utrecht, he went to Leiden to study Psychology in 2011. In 2015, he obtained his MSc degree with honors in Applied Cognitive Pscychology. Fascinated by the advancements being made in psychology within the field of traffic safety and vehicle automation, he joined SWOV Institute for Road Safety research for a short period of time.

In April 2016, Juan Pablo started his PhD on the interaction between automated vehicles and vulnerable road users at the Transport & Planning department of Delft University of Technology as a member of the NWO-VERDUS Spatial and Transport impacts of Automated Driving project (STAD). He assisted in teaching activities of the master course “Traffic Safety” and he supervised various master students’ theses. During his PhD, Juan Pablo joined the Institute of Transport Studies Leeds as a guest PhD researcher.

In July 2020, Juan Pablo joined Rijkswaterstaat where he currently works as an advisor in traffic safety. His main interests are traffic safety, vulnerable road users and smart mobility. Juan Pablo enjoys using the knowledge gained during his PhD to make the Dutch roads safer everyday.

Juan Pablo lives together with his wife Merlijn and his newborn daughter Lucía in Oegstgeest. In his free time, he enjoys spending time with family and friends, bouldering, photography and exploring new cuisines.

JOURNAL PUBLICATIONS

Núñez Velasco, J. P., de Vries, A., Farah, H., van Arem, B., & Hagenzieker, M. (2021). Cyclists' Crossing Intentions When Interacting with Automated Vehicles: A Virtual Reality Study. *Information, 12(1); 7.* https://doi.org/10.3390/info12010007

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Núñez Velasco, J. P., Lee, Y. M., Uttley, J., Solernou, A., Farah, H., van Arem, B., Hagenzieker, M., & Merat, N. (*Under review*). Will pedestrians cross the road before an Automated Vehicle? The Effect of Drivers' Attentiveness and Presence on Pedestrians' Road Crossing Behavior.

PEER-REVIEWD CONFERENCE CONTRIBUTIONS

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