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Studying pedestrians' crossing behavior when interacting with automated vehicles using virtual reality

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A B S T R A C T

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.

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

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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 et al., 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, 2017; Habibovic, Andersson, Nilsson, Lundgren, & Nilsson, 2016; Rodríguez Palmeiro et al., 2018; Rothenbücher, Li, Sirkin, Mok, & Ju, 2016; Vissers, van der Kint, van Schagen, & Hagenzieker, 2016). For example, Rothenbücher et al. (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, Toda, Sakamoto, & Igarashi, 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 AV's 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

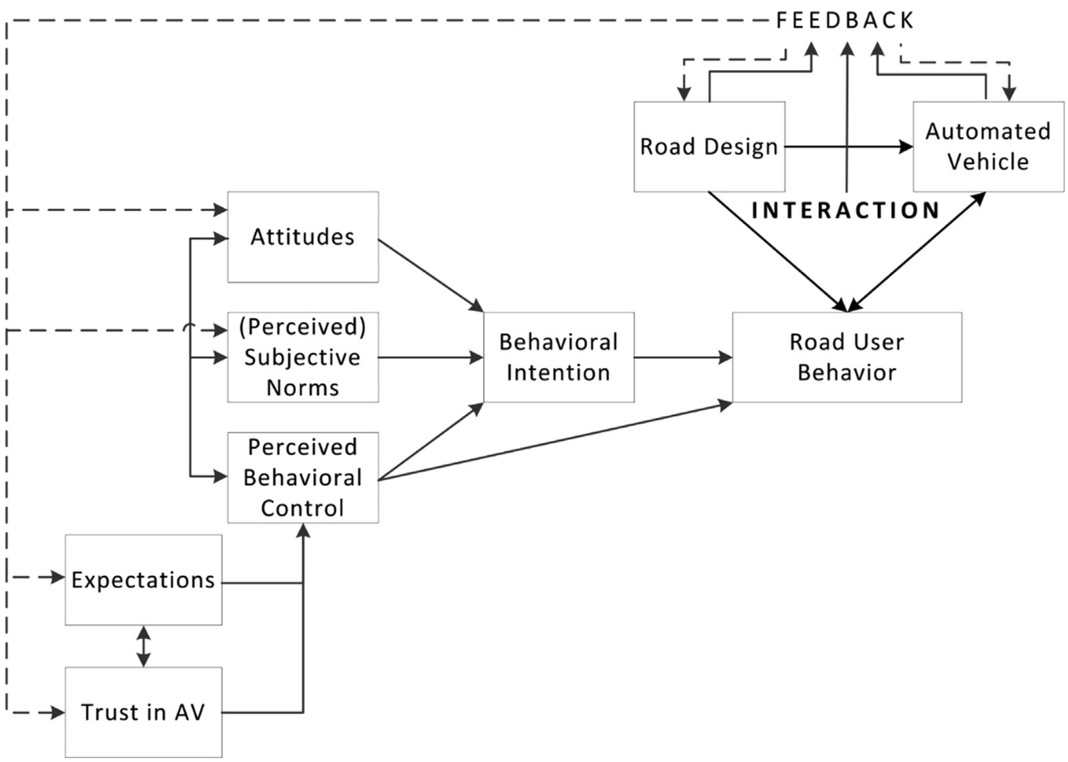

Fig. 1. Theoretical framework explaining the way AVs could affect VRUs' behavior (Nuñez Velasco et al., 2017).

understanding of psychological factors influencing the interactions between AVs and road users (Nuñez Velasco, Farah, Arem, & Hagenzieker, 2017), as illustrated in Fig. 1.

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.

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 $\times$ speed, 2 $\times$ time gap, and 2 $\times$ crossing facility) and 24 scenarios of the AV (2 $\times$ speed, 2 $\times$ time gap, 2 $\times$ crossing facility, and 3 $\times$ 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 s 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 s (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

Table 1
Variables included in this experiment.

Variable name	Levels	Annotation	Explanation
Vehicle type	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 s
		Gap4s (G4s)	Gap between vehicle and pedestrian was 4 s
eHMI*	2	Green sign (G)	The AV was equipped with a green sign on the front window
(see Fig. 1)		Red sign (R)	The AV was equipped with a red sign on the front window

Note: * eHMI was only shown on the AV.

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 (Nuñez Velasco et al., 2017) and previous studies (Kadali & Vedagiri, 2016; Kadali, Vedagiri, & Rathi, 2015), was considered to examine differences in crossing intentions of pedestrians.

2.1. Sample

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., 2017; Rodríguez Palmeiro et al., 2018; Rothenbücher et al., 2016). The age of the participants ranged between 21 and 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 min) 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.

2.2. Methods

2.2.1. VR experiment

The videos were recorded on a two-way street that is 8 m 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 m with a resolution of 3480×2160 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 1440×2560.

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 (Fig. 2): 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).

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 s 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 Fig. 3.

Fig. 2. 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).

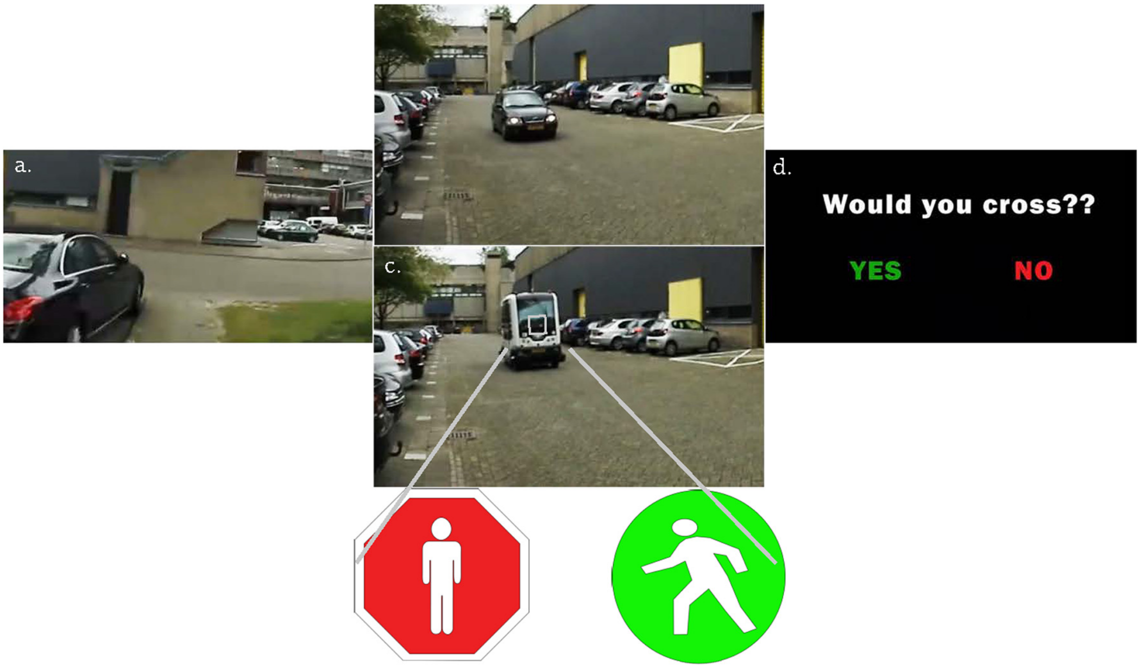

Fig. 3. Illustration of how a VR trial could look like. From left to right, it started with scene 'a' in which the participant appeared to walk towards the intersection. Scene b & c present two examples of the 32 scenarios. In this case scene 'b' shows the CV and 'c' the AV. Scene d prompted the pedestrians 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.

2.2.2. 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 5 (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 ($\alpha = 0.82$).

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., 2009).

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%.

2.3. 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 s. At the end of each scenario the following question appeared in the HMD; *'Would you cross?'* (see Fig. 4). 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 min 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 min per participant.

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.

3.1. 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), $\chi^2(1) = 0.586$, $p = .444$.

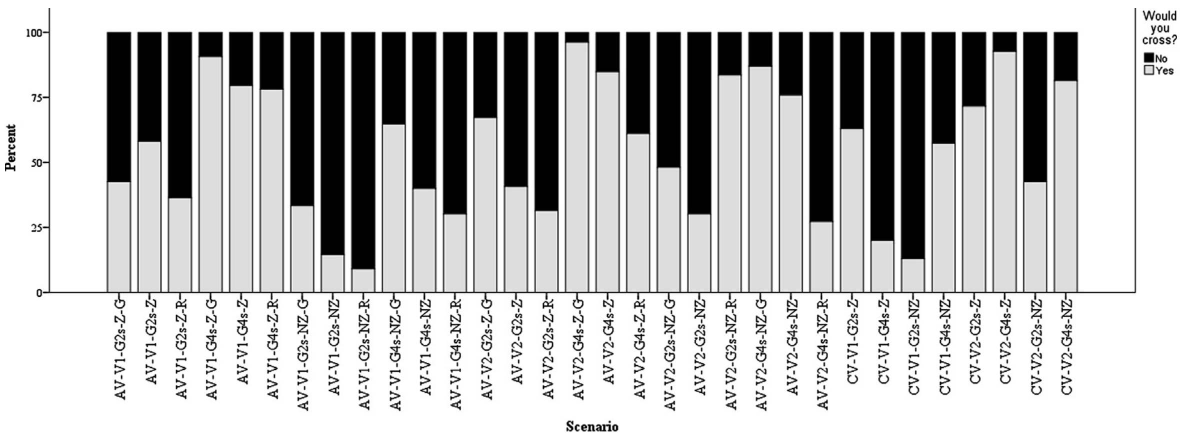

Fig. 4. Bar graph displaying the crossing intentions percentage per scenario. The annotation list can be found in Table 1.

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

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.

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 (Tables 3a and 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). Tables 2b and 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 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]	<0.001
$\beta_{VehicleType}$	Vehicle type				
(AV, CV*)	−0.02 (0.13)	0.98	[0.76, 1.26]	0.86	
β_{speed}	Speed				
(10, 20* km/h)	−0.94 (0.11)	0.39	[0.31, 0.49]	<0.001	
β_{Zebra}	Zebra crossing present				
(yes, no*)	0.89(0.11)	2.44	[1.96,3.04]	<0.001	
$\beta_{Gapsize}$	Gap size				
(seconds; 2 s, 4* s)	−1.21(0.11)	0.30	[0.24,0.37]	<0.001	
Random effects		Estimate (SE)	Z	p	
μ_0	ParticipantID: intercept (var)	0.92 (0.23)	4.07	<0.001	
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]	0.99
$\beta_{VehicleType}$	Vehicle type (AV, CV*)	−0.11(0.16)	0.90	[0.66,1.22]	0.49
β_{speed}	Speed (10, 20* km/h)	−0.98(0.11)	0.29	[0.23,0.36]	<0.001
β_{Zebra}	Zebra crossing present (yes, no*)	0.93(0.11)	0.38	[0.30,0.47]	<0.001
$\beta_{Gapsize}$	Gap size (2 s, 4 s*)	−1.26(0.12)	2.53	[2.02,3.17]	<0.001
$\beta_{GreenSign}$	Sign mounted (green sign, no sign*)	0.73(0.16)	2.08	[1.51,2.85]	<0.001
$\beta_{RedSign}$	Sign mounted (red sign, no sign*)	−0.44(0.16)	0.65	[0.47,0.88]	0.01
β_{Trust}	Trust in AVs	0.33(0.14)	1.30	[0.99,1.73]	0.02
$\beta_{Recognized}$	Recognized WEpod (yes, no*)	−0.31(0.31)	0.53	[0.29,0.98]	0.04
Random effects		Estimate (SE)	Z	*p*	
μ_0	ParticipantID: intercept (var)	0.88 (0.23)	3.905	<0.001	
Model performance					
−2LL	7998.6				
AIC	8000.6				
BIC	8006.1				

*Reference category.

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]	<0.001
$\beta_{\text{VehicleType}}$	Vehicle type (AV, CV*)	−0.02(0.13)	0.98	[0.76,1.26]	0.87
β_{speed}	Speed (10, 20* km/h)	0.27(0.15)	1.31	[0.97,1.75]	0.08
β_{Zebra}	Zebra crossing present (yes, no*)	0.89(0.11)	2.44	[1.96,3.04]	<0.001
β_{Gapsize}	Gap size (meters; 5.6 m, 22.2* m)	−2.42(0.23)	0.09	[0.06,0.14]	<0.001
β_{Gapsize}	Gap size (meters; 11.1 m, 22.2* m)	−1.25(0.16)	0.29	[0.21,0.39]	<0.001
Random effects		Estimate (SE)	*Z*	*p*	
μ_0	ParticipantID: intercept (var)	0.93 (0.23)	3.99	<0.001	
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]	0.96
$\beta_{VehicleType}$	Vehicle type (AV, CV*)	−0.11 (0.16)	0.90	[0.66,1.22]	0.49
β_{speed}	Speed (10, 20 km/h*)	0.28 (0.15)	1.32	[0.98,1.78]	0.07
β_{Zebra}	Zebra crossing present (yes, no*)	0.93 (0.11)	2.53	[2.02,3.17]	<0.001
β_{Gapsize}	Gap size (5.6 m, 22.2* m)	−2.52 (0.23)	0.08	[0.05,0.13]	<0.001
β_{Gapsize}	Gap size (11.1 m, 22.2* m)	−1.30 (0.17)	0.27	[0.20,0.38]	<0.001
$\beta_{GreenSign}$	Sign mounted (green sign, no sign*)	0.73 (0.16)	2.08	[1.51,2.85]	<0.001
$\beta_{RedSign}$	Sign mounted (red sign, no sign*)	−0.44 (0.16)	0.65	[0.47,0.88]	0.01
β_{Trust}	Trust in AVs	0.27 (0.14)	1.30	[0.99,1.73]	0.06
$\beta_{Recognized}$	Recognized WEpod (yes, no*)	−0.64 (0.31)	0.53	[0.29,0.98]	0.04
Random effects		Estimate (SE)	*Z*	*p*	
μ_0	ParticipantID: intercept (var)	0.93 (0.23)	3.986	<0.001	
Model performance					
-2LL	8000.2				
AIC	8002.2				
BIC	8007.6				

*Reference category.

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 2-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, $r = -0.737$, $p < 0.001$. 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 4. 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 m).

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. Fig. 5 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.

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 5 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.

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

Table 4
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]	<0.001
$\beta_{VehicleType}$	Vehicle type (AV, CV*)	−0.10 (0.44)	0.90	[0.38,2.14]	0.82
β_{speed}	Speed (10, 20 km/h*)	−0.03 (0.42)	0.97	[0.43,2.19]	0.93
β_{Zebra}	Zebra crossing present (yes, no*)	−0.40 (0.32)	0.96	[0.52,1.79]	0.90
$\beta_{Gapsize}$	Gap size (5.6 m, 22.2* m)	−1.24 (0.62)	0.29	[0.09,0.99]	0.05
$\beta_{Gapsize}$	Gap size (11.1 m, 22.2* m)	−0.41 (0.46)	0.66	[0.27,1.64]	0.37
$\beta_{GreenSign}$	Sign mounted (green sign, no sign*)	0.45 (0.44)	1.57	[0.66,3.76]	0.31
$\beta_{RedSign}$	Sign mounted (red sign, no sign*)	−0.50 (0.42)	0.61	[0.27,1.39]	0.24
β_{Trust}	Trust in AVs	0.54 (0.21)	1.71	[1.14,2.56]	0.01
$\beta_{Recognized}$	Recognized WEpod (yes, no*)	−0.13 (0.43)	0.88	[0.38,2.03]	0.76
β_{PBC}	PBC	−2.18 (0.19)	0.11	[0.08,0.16]	<0.001
Random effects		Estimate (SE)	*Z*	*p*	
μ_0	ParticipantID: intercept (var)	0.74 (0.37)	1.99	0.05	
Model performance					
-2LL	3476.1				
AIC	3478.1				
BIC	3482.5				

*Reference category.

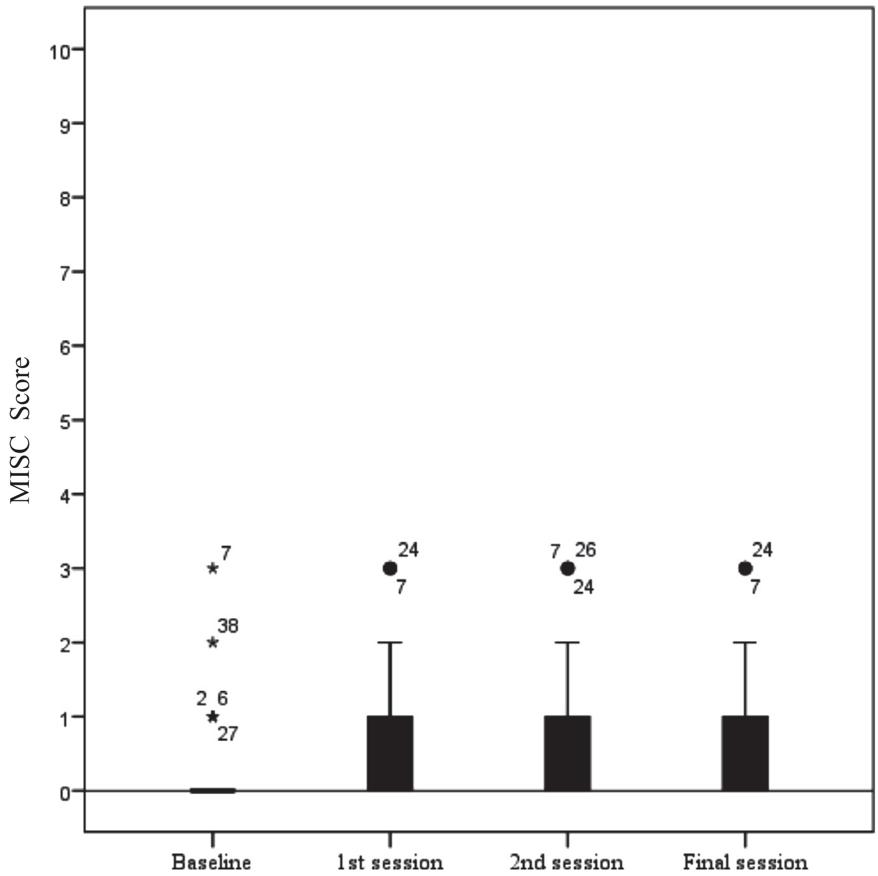

Fig. 5. Boxplot representing the MISC results before and after each VR session. On the y-axis the MISC score is plotted. The numbers represent the participant's number.

Table 5
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

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., 2017; 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., 2017) 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 s as compared to 2 s 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 min 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 (Nuñez 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.

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.

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