Blinded windows and empty driver seats: The effects of automated vehicle characteristics on cyclists' decision-making

P. Bazilinskyy[1], D. Dodou[1], Y. B. Eisma[1], W. Vlakveld[2], J. C. F. de Winter[1]

[1] Delft University of Technology, Delft, the Netherlands
[2] SWOV, The Hague, the Netherlands

Correspondence concerning this article should be addressed to Pavlo Bazilinskyy, Department of Cognitive Robotics, Faculty of Mechanical, Maritime and Materials Engineering, Delft University of Technology, Mekelweg 2, 2628 CD Delft, the Netherlands. E-mail: p.bazilinskyy@tudelft.nl

Abstract

Automated vehicles (AVs) may feature blinded windows and external Human-Machine Interfaces (eHMIs), and the driver may be inattentive or absent. How these features would affect cyclists is unknown. In Experiment 1, 1260 participants viewed images of approaching vehicles from a cyclist's perspective and decided whether to brake or continue pedalling. The images depicted (1) an AV with an eHMI 'GO' on the roof, an AV without eHMI, or a traditional vehicle, (2) with the driver present, driver absent, or with blinded windows, (3) about to cross the cyclist' path, (4) in visually simple or complex surroundings, and (5) at five distances (urgency levels) from the cyclist. The eHMI and urgency level had a strong impact on crossing decisions, whereas the visual complexity of the surroundings had no significant influence. Blinded windows caused participants to brake for the traditional vehicle. These effects were replicated in Experiment 2 (*n* = 1086), which also required participants to detect vehicle features. The eHMI 'GO' and blinded windows yielded high detection rates, whereas the detectability of the driver was scenario-dependent. The driver's eye contact caused participants to continue pedalling. To conclude, blinded windows cause cyclists to brake and driver eye contact stimulates cyclists to continue.

Keywords: cycling; automated driving; driver; external human-machine interface

Introduction

About 70% of cycling fatalities occur as a result of a collision with a motorized vehicle (SWOV, 2017). A typical scenario is that the cyclist has right of way, and the approaching vehicle hits the cyclist perpendicularly at a road crossing (Räsänen & Summala, 1998; Schepers, 2011). Common causes of such accidents are the driver's failure to check the vehicle's blind spot, improper visual scanning, and inattentiveness (Habibovic & Davidson, 2012; Räsänen & Summala, 1998; Sundfør et al., 2019). Automated vehicle (AV) technology could prevent these types of accidents by detecting the cyclist and adhering to the traffic rules by braking in time (Li & Kockelman, 2016; Silla et al., 2017).

Although AVs have the potential to prevent accidents, there is a risk that AVs may cause confusion or uncertainty on behalf of vulnerable road users (Deb et al., 2018a, 2018b; Jayaraman et al., 2019). In automated driving of SAE Level 3 and above (SAE International, 2018), the person in the driver seat may not be paying attention to the road, whereas in Levels 4 and 5 automation, the driver seat might be empty (Waymo, 2019) or the vehicle may feature a novel seating configuration without a driver seat at all (e.g., Mercedes-Benz, 2015; Volvo, 2018). In these cases, driver communication sources, such as eye contact, will be absent. Additionally, technology is under development that allows adjustment of window tinting or the windows to be used as displays (Continental, 2019; Jones et al., 2020; Matsumura & Kirk, 2017; Sen & Sener, 2020). These developments could prove useful for future AVs in which the occupants may want to customize their ride experience and secure privacy (Lekach, 2019). Currently, tinting of the windshield is prohibited in many countries or allowed to a limited extent, where typically a minimum visible light transmittance of 70% of 75% is used; at the same time, the permitted degree of blinding of the front side window varies greatly, from entirely banned down to only 20% light transmittance (e.g., Matsumura, 2017). Although fully blinded windows are currently not allowed, it is possible that these rules will be relaxed when driverless vehicles are deployed in which there is no benefit for other road users to see the vehicle occupants. As of present, it is unknown how blinded windows would influence the decision-making of other road users, but it can be expected that blinded windows cause some confusion and hesitation.

Apart from the above characteristics of AVs, many current AVs are distinguishable from traditional vehicles by a lidar on the roof, distinctive branding, or 'self-driving' signs (e.g., Uber, 2020; Waymo, 2019). Previous online research suggests that cyclists are more certain that the vehicle has seen them if the vehicle is recognisable as an AV compared to when it is not (Rodríguez Palmeiro et al., 2018). These effects may be attributed to the fact that the omnidirectional sensors of an AV are able to detect the cyclist in the driver's blind spot (Rodríguez Palmeiro et al., 2018). More research is still needed to determine whether cyclists would behave more cautiously or less cautiously when encountering an AV compared to a traditional vehicle.

Several studies suggest that AVs should communicate using external Human-Machine Interfaces (eHMIs). eHMIs can take various forms, including screens and light bars that depict instructions (e.g., Deb et al., 2016; De Clercq et al., 2019; Fridman et al., 2017; Hudson et al., 2019), intentions (e.g., Deb et al., 2016; Habibovic et al., 2018; Kaß et al., 2020), or the automation mode (e.g., Faas et al., 2020; Joisten et al., 2019). Studies have shown that compared to AVs without eHMI, pedestrians feel safe and better informed when an eHMI is present (Ackermans et al., 2020; Faas et al., 2020; Habibovic et al., 2018) and are more inclined to cross when an eHMI indicates so (e.g., Ackermans et al., 2020; Dietrich et al., 2020; Hudson et al., 2019; Kooijman et al., 2019). However, other studies showed that the effect of eHMIs is small compared to the effect of vehicle motion (e.g., Cefkin et al., 2019; Chen et al., 2020; Clamann et al., 2017).

The efficacy of eHMIs may depend on the amount of visual information to be processed. Even though an eHMI may provide direct instructions or suggestions to a road user, the road user will still have to verify whether the eHMI's message is valid by counterchecking the message with other cues in the environment. It could be overwhelming for a road user to make a crossing decision based on traffic rules, hazards, the driver's presence and its behaviour, and the eHMI message all at the same time. Visual demands could be particularly high if the environment is cluttered, such as in a city. A laboratory-based study by Tapiro et al. (2020) showed that a visually dense environment led to missed crossing opportunities and visual attention dispersion by pedestrians. By extension, it is conceivable that eHMIs may be less effective in environments of higher visual complexity.

Study Aims

Cycling safety is a concern in the Netherlands and many other countries (European Commission, 2015). As noted above, even though the cyclist may be moving on a designated bike path and have priority, it still regularly happens that the cyclist is hit because the driver of an approaching vehicle overlooks the cyclist or because the cyclist misunderstands the vehicle's intentions (Kovácsová et al., 2019).

In a previous online study, Vlakveld et al. (2020) presented participants with animated video clips from a cyclist's perspective. In each video clip, a vehicle was on a collision course with the cyclist, for different vehicle types (automated with eHMI 'GO', automated without eHMI, traditional vehicle) and urgency levels. Of each conflict type, three versions of the video clips were made that differed regarding the moment the video ended, thus creating videos with an early, mid, and late moment for the cyclist to decide to continue pedalling or to slow down. The goal of Vlakveld et al.'s study was not to test cycling behaviour in near-crash situations; after all, in each video, the cyclist had right of way, and there was still sufficient time for the approaching road users to come to a complete stop. Rather, the goal was to examine the extent to which the vehicle's characteristics and urgency of the situation contribute to cyclists' decision-making. The results of Vlakveld et al.'s study showed that participants more often decided to slow down when the approaching vehicle was an AV compared to when it was a traditional vehicle. However, when the approaching AV's eHMI communicated 'GO', they were less likely to slow down compared to a traditional vehicle. Furthermore, the higher the urgency (i.e., the later the decision moment), the more often participants decided to slow down. Although the study of Vlakveld et al. is informative about the effects of vehicle appearance and urgency, the effects of the visibility of the driver, eye contact, driver presence, and visual complexity of the surroundings are yet to be established.

The aim of the current study was two-fold. First, we aimed to replicate the effects observed in Vlakveld et al. (2020) regarding urgency level and vehicle type. More specifically, the study of Vlakveld et al. (2020) was conducted using Dutch participants; we aimed to examine whether the findings replicate in an international sample of participants. Our second aim was to examine the effects of blinded windows, driver presence, eye contact, and visual complexity of the surrounding environment. In our study, we measured not only brake/continue decisions (as was done by Vlakveld et al., 2020), but also participants' response times.

Based on our previous research, in which we used static stimuli (Bazilinskyy et al., 2020a) as well as animated video clips (Bazilinskyy et al., 2021; Eisma et al., 2020), we opted for a hybrid video-image approach with demonstration video clips (as used in Vlakveld et al., 2020) to give the participants a sense of the speed of the cyclist and approaching vehicle, followed by still images to which the participant had to respond. The advantage of using images is that they allow for controlled comparisons; with video clips, on the other hand, the situation is continuously evolving, which may introduce additional sources of variance.

Two experiments were conducted. In Experiment 1, participants were asked to decide whether they would brake or continue pedalling. In Experiment 2, participants were again asked to make this decision and were also asked questions after each image whether they had recognised specific AV features in the image, such as the driver and the blinded windows. Experiment 2 served to replicate Experiment 1, and acted as a validation check regarding whether participants acted based on what they saw in the image.

Experiment 1

Method

Stimuli

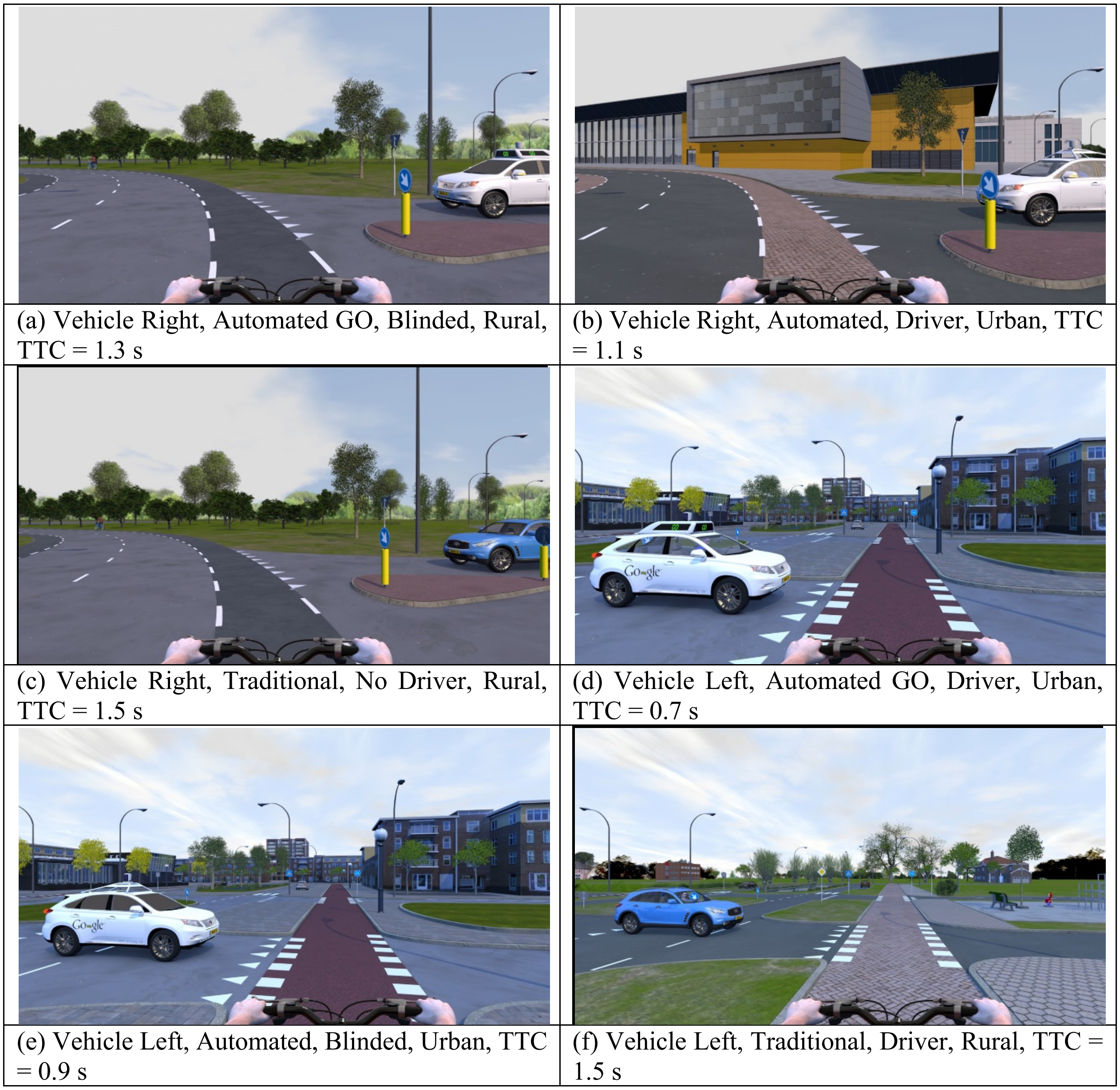
In total, 180 image stimuli were created: 2 traffic conflict types x 3 vehicle types x 3 window types x 2 visual complexity levels of the surroundings x 5 urgency levels. The images showed a traffic situation from a cyclist's perspective with an approaching vehicle. The traffic situation concerned an intersection without traffic lights and with a designated cycling path. Shark teeth were present on the road, meaning that the cyclist had right of way. The selected types of conflict are known to frequently result in bicycle-vehicle crashes (e.g., Räsänen & Summala, 1998; Schepers et al., 2011). The images in which the driver was present were frames extracted from videos used in Vlakveld et al. (2020). The driver was removed, or the windows were blinded using Adobe Photoshop.

The experimental conditions are detailed in Table 1. Figure 1 shows examples of the images, featuring the three vehicle types, two visual complexity levels of the surroundings, and three of the five urgency levels. Note that the presence of the turn indicator and eye contact varied naturalistically with the progression of the driving scene, as in the videos used by Vlakveld et al. (2020). Table 2 provides an overview of the covariates (turn indicator, eye contact) of the five urgency levels. Experiment 2 investigates the effect of eye contact in a controlled manner.

Table 1. Description of the experimental conditions.

Type	Condition	Description

Conflict	Vehicle Left	The vehicle approached the intersection from the left and was about to cross the cycling path. The cycling path was separated from the main road by a lawn or pavement.
	Vehicle Right	The vehicle approached the intersection from the right and was about to cross the cycling path. The lane on which the vehicle was driving was separated by a verge with sign on a pole.
Vehicle	Automated GO	A white vehicle with a sticker 'Google' on its side, a sensory tower on its roof, and an eHMI on the roof with the message 'GO'.
	Automated	A white vehicle with a sticker 'Google' on its side, a sensory tower on its roof, and no eHMI. As Vlakveld et al. (2020) pointed out, the automated Google vehicle in the videos is no longer in use. Nowadays, these vehicles are called Waymo and look differently. However, we assumed that participants would associate the Google logo with AVs.
	Traditional	A blue vehicle with no sticker, no sensory tower, and no eHMI. The traditional vehicle had a different (but still neutral) colour and a different brand than the AVs, because our goal was to assess the effect of AV appearance relative to a traditional vehicle in its entirety (i.e., not just testing the effect of the stickers or sensory tower).
Windows	Driver	Transparent windows, with a driver present. In SAE Level 3 automation and above, the driver is likely not to pay attention to the driving task. Accordingly, for the Automated and Automated GO vehicles, the 'driver' stared downwards (suggesting he was texting) and was relatively hard to see for the cyclist. The driver of the traditional vehicle looked straight ahead and turned his head in the direction of the cyclist when approaching the intersection (see Table 2).
	Blinded	Blinded windows, as a result of which no driver was visible.
	No Driver	Transparent windows, no driver present. This condition may occur in SAE Level 4 or 5 automation.
Visual complexity of surroundings	Rural (low)	A rural road with greenery and a few buildings.
	Urban (high)	An urban road with buildings in the style of a European city centre. Note that the road layout was the same for the rural and urban road; only the visual surroundings were changed.
Urgency (time to conflict, TTC)	1.5 s 1.3 s 1.1 s 0.9 s 0.7 s	Urgency was varied by extracting frames from the video with 0.2 s increments. The distance between the location of the vehicle for two consecutive urgency levels was about 0.78 m (corresponding to a driving speed of 14 km/h). A TTC of 0.7 s corresponds to the moment of the smallest distance to the vehicle; at this moment, the front of the vehicle was about 2.6 m from the estimated collision point (centre of the cycling path). In theory, at 14 km/h, the approaching vehicle could come to a full stop in 0.5 s (assuming a deceleration of 8 m/s^2), and hence even for the short TTC of 0.7 s, it may still be ambiguous to the cyclist whether or not the car would stop in time. Note that at TTC = 0.7 s, the cyclist would crash into the side of the vehicle after about 2.5 s if the cyclist would not brake (based at Vlakveld et al., 2020).



(a) Vehicle Right, Automated GO, Blinded, Rural, TTC = 1.3 s

(b) Vehicle Right, Automated, Driver, Urban, TTC = 1.1 s

(c) Vehicle Right, Traditional, No Driver, Rural, TTC = 1.5 s

(d) Vehicle Left, Automated GO, Driver, Urban, TTC = 0.7 s

(e) Vehicle Left, Automated, Blinded, Urban, TTC = 0.9 s

(f) Vehicle Left, Traditional, Driver, Rural, TTC = 1.5 s

Figure 1. Examples of image stimuli (6 selected images of 180 images used in the experiment).

Table 2. Description of covariates of the urgency factor.

Vehicle Right			**Vehicle Left**		
TTC	**Turn indicator**	**Eye contact**[a]	**TTC**	**Turn indicator**	**Eye contact**[a]
1.5 s	Off	Yes	1.5 s	Off	Yes
1.3 s	Off	No (head turning)	1.3 s	Off	No
1.1 s	Off	No	1.1 s	Off	No
0.9 s	On	No	0.9 s	Off	No
0.7 s	On	No	0.7 s	Off	No

[a]Eye contact only for the Traditional vehicle. TTC = time to conflict.

Crowdsourcing Experiment

The research was approved by the Human Research Ethics Committee of the TU Delft. The participants subscribed to the online study through the crowdsourcing service Appen (https://appen.com). Participants became aware of this research through one of many channel websites (e.g., https://www.ysense.com) where our study was available in a list of other projects available for completion. We allowed 2000 contributors from all countries to participate. It was not permitted to complete the study more than once with the same worker ID. A payment of USD 0.30 was offered for the completion of the study. The experiment was created using jsPsych (i.e., https://www.jspsych.org; De Leeuw, 2015).

On the top of the page, contact information was provided, and the purpose of the study was described as "*to investigate how cyclists respond to approaching cars*". Participants were informed that they could contact the investigators to ask questions about the study and that they had to be at least 18 years old. Information about anonymity and voluntary participation was provided as well. Participants first answered demographic questions, such as about age, gender, and driving experience. They were then asked to leave the questionnaire by clicking on a link that opened a webpage with the experiment and were presented with the following instructions: "*In the following images, you will see a traffic situation from the perspective of a cyclist. In each image, a car is approaching you. Sometimes this car is a self-driving car, and sometimes it is a normal car. Your task is to indicate what you, as a cyclist, would do: Brake (press 'B') or Continue Pedaling (press 'P'). You will view 90 images. Observe the scene carefully before pressing the 'B' or 'P' key.*" The participants were not given information about the eHMI, road signage, or applicable traffic rules, and were not instructed to respond as fast as possible.

The participants had to respond to a random 90 of the 180 images presented in three batches of 30 images in random order. In other words, each image was seen by about 50% of the participants. Participants were exposed to 90 instead of all 180 images to limit the total duration of the experiment. Below each image, it was mentioned: "*Imagine that you are the cyclist. Press 'B' if you would brake, press 'P' if you would continue pedaling.*" Before each batch of images, the participants were shown an example video from a randomised set of six videos (Automated GO, Automated, and Traditional vehicle, in the Vehicle Left or Vehicle Right conflicts), which allowed them to get an indication of the speed of the vehicle and the cyclist. In the videos, the vehicle was moving at a speed of approximately 14 km/h, and the speed of the bicycle was approximately 17 km/h. The example videos depicted the same vehicle types as the image stimuli, with transparent windows and driver present, but in different surroundings (outskirts of a town) and traffic situation. After each batch of images, participants were shown the following text: "*You have now completed 30 [60] images out of 90. When ready press 'C' to proceed to the next batch*." At the end of the experiment, the participants were shown a unique code. They were required to enter the code as proof that they completed the experiment to receive their remuneration.

An important question in empirical research is what the unit of analysis should be. In educational research, for example, it has to be decided whether the unit of analysis is 'students', 'classes', or 'schools' (e.g., Barcikowski, 1981). In the present study, the unit of analysis was 'images' (instead of 'participants'). The reason is that (1) we were interested in understanding differences between images, and (2) there were a large number of images (n = 180) with many participants per image. We calculated, for each of the 180 images, the percentage of participants who indicated they would brake and the median response time across participants. Multiple regression analyses were performed to examine which image characteristics were predictive of the percentage of participants who indicated they would brake and the median response time across participants.

In cases where we compared the percentage of participants who braked between image conditions (e.g., images with the driver visible vs. blinded windows vs. no driver), we used within-subject confidence intervals, computed at the level of participants (Morey, 2008). In short, this approach involves subtracting the participants' grand mean before computing confidence intervals. Confidence intervals were calculated based on a normal distribution, an assumption that seems legitimate for typical binary response data, especially when responses are averaged over multiple trials (Brown et al., 2001).

Results

The 2000 participants took part between 2 and 4 May 2020. After the survey, participants had the option to complete a satisfaction survey offered by the crowdsourcing service Appen. This survey allows researchers to judge whether participants found the task and its instructions clear and the payment satisfactory. Results of this survey showed an overall satisfaction rating of 4.3 on a scale from 1 (‘*very dissatisfied*’) to 5 (‘*very satisfied*’) (103 participants completed this optional survey).

Before proceeding with the analysis, we removed participants who appeared not to have taken the task seriously (i.e., participants who indicated not to have read the instructions and participants who completed the study in less than 5 min) and participants with incomplete data (e.g., due to database storage errors). Furthermore, if it appeared that a participant conducted the study more than once from the same IP address, only the first response of that participant was kept. In total, 740 of 2000 responses were removed, leaving 1260 participants. A mapping error had occurred, where one of the 180 images (Vehicle Left, Traditional, Blinded, Urban, TTC = 1.5 s) was shown instead of another image (Vehicle Left, Traditional, Driver, Urban, TTC = 1.5 s) for the first 293 participants. The data for this image for these participants (0.08% of the total data) were removed.

The sample consisted of 830 males, 427 females, and 3 participants who selected ‘I prefer not to respond’ to the gender question. The mean age of the participants was 36.5 years (SD = 11.5). The participants resided in 63 countries, with the most represented countries being Venezuela (n = 544), USA (n = 75), Russia (n = 71), Egypt (n = 63), and Ukraine (n = 59).

First, the percentage of participants who indicated that they would brake (called henceforth braking percentage) was computed for each of the 180 images. These percentages ranged between 28.2% (Vehicle Right, Automated GO, No Driver, Urban, TTC = 1.5 s) and 82.3% (Vehicle Left, Traditional, Driver, Urban, TTC = 0.7 s). The overall mean of the braking percentage of the 180 images was 58.9%, and the standard deviation was 14.0%.

The results of the regression analysis for the braking percentage are provided in Table 3. These results show that the baseline braking percentage was 59.6%, with the Vehicle Right conflicts yielding a 16.8% lower braking percentage than the Vehicle Left conflicts. For every 0.2 s reduction in TTC, the percentage braking increased by 6.0%. Moreover, Automated GO yielded a 13.6% lower braking percentage than the Traditional vehicle. The conflict type (β = 0.605), urgency level (β = 0.612), and Automated GO (β = -0.462) had the strongest effects on the braking percentage. The effects of visual complexity of the surroundings, vehicle type, and window type were comparatively small ($|\beta| \leq 0.03$), contributing with less than 1% to the braking percentage. The independent variables combined predicted the braking percentage with high accuracy (r = 0.977, r^2 = 0.954).

The effects of the three strongest predictor variables are illustrated in Figure 2. It can be seen that the urgency level had a monotonic effect, with the braking percentage increasing with increasing urgency. The Vehicle Left conflict caused more participants to brake than the Vehicle Right conflict. The automated GO images stimulated people to continue pedalling, an effect found in the Vehicle Left as well as Vehicle Right conflicts. In the least urgent condition (TTC = 1.5 s), the driver of the Traditional vehicle made eye contact. No consistent effects of eye contact (relative to the vehicle type or to the other urgency levels without eye contact) can be distinguished in Figure 2.

The median response times per image ranged between 1033 ms (Vehicle Left, Automated GO, No Driver, Urban, TTC = 0.7 s) and 1375 ms (Vehicle Left, Traditional, No Driver, Rural, TTC = 1.5 s). The overall mean of the median response times of the 180 images was 1186 ms, and the standard deviation of these 180 images was 69 ms.

The results of the regression analysis for the median response time (Table 4) mirror those of the braking percentage. That is, faster responses (28 ms faster for each 0.2 s reduction of TTC) were found for more urgent situations, for the Vehicle Right as compared to the Vehicle Left conflict (29 ms faster), for Automated GO as compared to the Traditional vehicle (42 ms faster), and for Blinded windows compared to the Driver (30 ms faster). The predictive accuracy of the median response time was strong (r = 0.726, r^2 = 0.528), but less strong than the abovementioned predictions for the braking percentage. Images that yielded a higher braking percentage yielded a faster median response time (r = -0.30, p < 0.001, n = 180).

Table 3. *Regression model statistics for prediction of the braking percentage (n = 180).*

Predictor	**B**	**β**	***t***	***p***
Constant	59.646			
Conflict (0 = Vehicle Left, 1 = Vehicle Right)	-16.838	-0.605	-36.807	<0.001
Urgency (0 = 1.5 s, 4 = 0.7 s)	6.028	0.612	37.270	<0.001
Visual complexity (0 = Rural, 1 = Urban)	0.364	0.013	0.796	0.427
Vehicle (0 = Traditional, 1 = Automated GO)	-13.634	-0.462	-24.335	<0.001
Vehicle (0 = Traditional, 1 = Automated)	-0.133	-0.004	-0.237	0.813
Windows (0 = Driver, 1 = No Driver)	-0.734	-0.025	-1.310	0.192
Windows (0 = Driver, 1 = Blinded)	0.890	0.030	1.588	0.114

$F(7,172) = 504.98$, $p < 0.001$, $r = 0.976$, $r^2 = 0.954$.

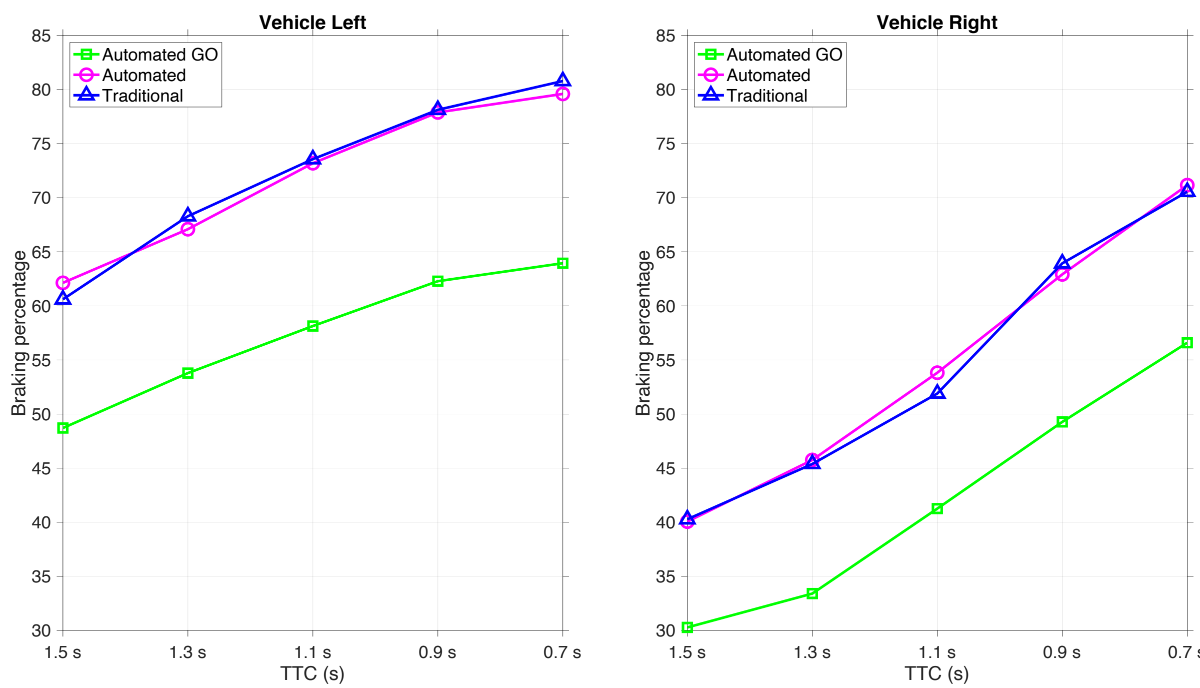


Figure 2. Braking percentage, as a function of conflict type (Vehicle Left vs. Vehicle Right), urgency level (TTC = 1.5 s: low urgency, TTC = 0.7 s: high urgency), and vehicle type (Automated GO, Automated, Traditional).

Table 4. *Regression model statistics for prediction of the median response time in milliseconds (n = 180).*

Predictor	***B***	**β**	***t***	***p***

Constant	1255.7			
Conflict (0 = Vehicle Left, 1 = Vehicle Right)	29.1	0.213	4.064	<0.001
Urgency (0 = 1.5 s, 4 = 0.7 s)	-27.9	-0.578	-11.027	<0.001
Visual complexity (0 = Rural, 1 = Urban)	-11.0	-0.081	-1.537	0.126
Vehicle (0 = Traditional, 1 = Automated GO)	-41.9	-0.289	-4.776	<0.001
Vehicle (0 = Traditional, 1 = Automated)	9.1	0.063	1.038	0.301
Windows (0 = Driver, 1 = No Driver)	-5.8	-0.040	-0.666	0.507
Windows (0 = Driver, 1 = Blinded)	-30.2	-0.208	-3.442	0.001

$F(7,172) = 27.46$, $p < 0.001$, $r = 0.726$, $r^2 = 0.528$.

As shown in Tables 3 and 4, the largest effects were found for conflict type, urgency level, and Automated GO versus the Traditional vehicle. Considerably smaller effects were found for the No Driver and Blinded windows conditions. These effects were not statistically significant at the level of the images ($n = 180$, see Table 3), but were explored in further depth at the level of participants ($n = 1260$). Figure 3 shows the effects on the braking percentage as a function of the three window conditions (Driver, No Driver, Blinded) and the three vehicle conditions (Automated GO, Automated, Traditional).

Two patterns can be distinguished. First, the vehicle Automated GO with No Driver caused participants to continue pedalling compared to the Automated GO vehicle with a Driver or with Blinded windows. In other words, the eHMI appeared to work best when there was no driver. Secondly, the Traditional vehicle with Blinded windows caused participants to brake.

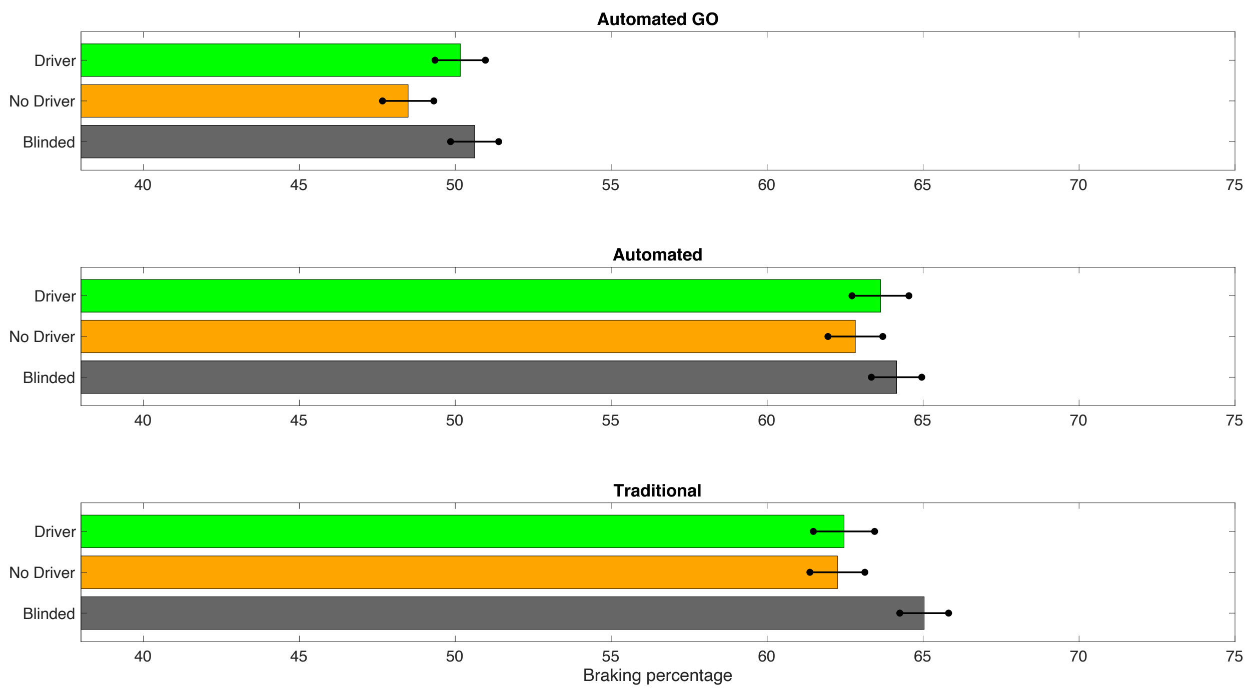


Figure 3. Percentage of 1260 participants who indicated that they would brake, as a function of window type (Driver, No Driver, Blinded) and vehicle type (Automated GO, Automated, Traditional) (20 responses for urgency level, visual complexity of the surroundings, and conflict type were averaged; on average participants viewed 50% of the images). The error bars represent within-subject confidence intervals, calculated for the three vehicle types separately (Morey, 2008).

A possible validity threat is that the present study was conducted among participants from many different countries, including countries without established cycling culture. Figure S1 in the Supplementary Material provides a subgroup analysis for participants whose primary self-reported transport mode was walking/cycling (n = 126) versus other participants (n = 1134). There were no substantial differences between these two groups. Additionally, regression analyses were conducted for participants from the most highly represented countries (see Figure S2). The results showed that although there were several significant differences in effect sizes between the different countries, the signs of the effects for conflict type, urgency level, and Automated Go were the same for Venezuela, the USA, Russia, Egypt, Ukraine, and the remainder of the countries combined.

Experiment 2

Method

The results of Experiment 1 showed that blinded windows caused cyclists to brake, and that the absence of a driver increased the effectiveness of the eHMI 'GO' (i.e., fewer cyclists braked). However, these theoretically relevant effects were small and on the verge of statistical significance, suggesting a need for replication. Furthermore, a limitation of Experiment 1 was that the effect of eye contact was not controlled but rather co-varied with urgency level. Additionally, it was unknown whether specific features of the stimuli, such as (absence of) the driver in the vehicle, were noticeable.

Therefore, the study was repeated using a subset of 36 of the 180 stimuli. Only urban surroundings and two of the five urgency levels (TTC = 1.5 s and TTC = 0.7 s) were used. Accordingly, the 36 images, which differed in terms of conflict type (Vehicle Left, Vehicle Right), vehicle (Automated GO, Automated, Traditional), Windows (Driver, Blinded, No Driver), and urgency (1.5 s, 0.7 s), were used. Four additional images were created so that eye-contact was manipulated (i.e., eye-contact vs. no eye-contact) for the following four images of the Traditional vehicle: Vehicle Left – TTC = 1.5 s, Vehicle Left – TTC = 0.7 s, Vehicle Right – TTC = 1.5 s, and Vehicle Right – TTC = 0.7 s. Figure 4 provides an example of eye-contact manipulation (Vehicle Left –TTC = 0.7 s). Before each batch of 10 images, the participants were shown an example video from a randomised set of four videos (the Automated GO and Traditional vehicle videos, in the Vehicle Left or Vehicle Right conflicts, also used in Experiment 1).

A payment of USD 0.20 was offered for the completion of the study. A total of 1568 participants took part between 25 November and 19 December 2020. Results of this survey showed an overall satisfaction rating of 4.0 on a scale from 1 ('*very dissatisfied*') to 5 ('*very satisfied*') (n = 111).

Figure 4. Vehicle Left, TTC = 0.7, without eye contact (left) and with eye contact (right).

After the participant provided the Braking (B) or Continue Pedalling (P) response, the image disappeared, and the following questions were shown on the same page:

- The windows of the car were blinded.
- There was a message 'GO' on the car.

- There was a sticker and sensor on the car.
- A driver was visible in the car.

Participants were required to answer these four questions based on what they had memorised from the previously shown image. The four questions were presented in random order, and each had the response options ‘True’ and ‘False’.

Results

A total of 1086 participants were retained after filtering, of which 286 had participated in Experiment 1. The sample consisted of 668 males, 414 females, and 4 participants who selected ‘I prefer not to respond’ to the gender question. The mean age of the participants was 37.2 years ($SD = 11.4$). The participants resided in 63 countries, with the most represented countries being Venezuela ($n = 471$), USA ($n = 50$), India ($n = 44$), Russia ($n = 42$), and Turkey ($n = 41$).

The results of the regression analysis for the braking percentage and the median response time ($n = 36$ images without eye contact) are provided in the Supplementary Material (Tables S1 & S2). An overview of the results for each of the stimuli separately is provided in the Supplementary Material as well (Table S3). The results of Experiment 2 can be summarised as follows:

- The effect of conflict (0 = Vehicle Left, 1 = Vehicle Right) on the braking percentage was weaker than in Experiment 1 (B = -16.838 in Experiment 1 vs. B = -6.384 in Experiment 2).
- The effect of Automated GO compared to the Traditional vehicle on the braking percentage was stronger than in Experiment 1 (B = -13.634 in Experiment 1 vs. B = -25.709 in Experiment 2).
- The effect of Blinded windows versus Driver on the braking percentage was significant and stronger than in Experiment 1 (B = 0.890 in Experiment 1 vs. B = 4.978 in Experiment 2). Figure 5 illustrates that blinded windows caused participants to brake, except for the Automated GO condition. Similarly, the absence of a driver caused participants to brake, except for the Automated GO condition.
- Participants took considerably longer (5381 ms, see Table S2) to provide their braking/pedalling response as compared to Experiment 1 (1256 ms, see Table 4).
- 42–73% of participants correctly recognised the stickers and sensor on the vehicle, while false-positive rates were 5–12%.
- 83–92% of participants correctly recognised that the vehicle had blinded windows, while false-positive rates were 9–21%.
- 81–90% of participants correctly recognised that there was a message GO on the vehicle, while false-positive rates were 3–21%. High false-positive percentages occurred in the Vehicle Left scenarios, where the word GO was part of the word Google on the vehicle’s body (see Figure 1).
- 55–98% of participants correctly recognised that there was a driver in the vehicle, while false-positive rates were 5–16%.
- Driver eye-contact increased the percentage of participants who continued pedalling by 8 to 11%, except for the Vehicle Right – TTC = 1.5 s condition, where the driver was hard to see (see Figure 1). These effects are illustrated in Figure 6.

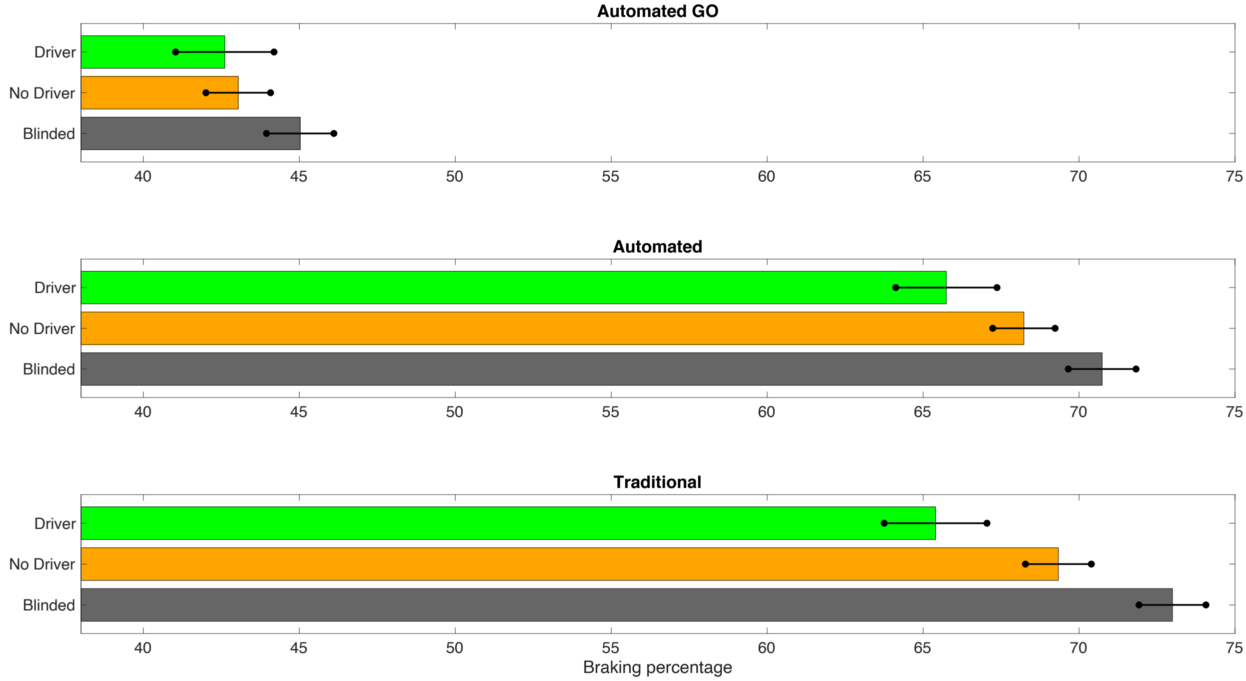


Figure 5. Braking percentage (n = 1086), as a function of window type (Driver, No Driver, Blinded) and vehicle type (Automated GO, Automated, Traditional) (4 responses for urgency level and conflict type were averaged). The error bars represent within-subject confidence intervals, calculated for the three vehicle types separately (Morey, 2008).

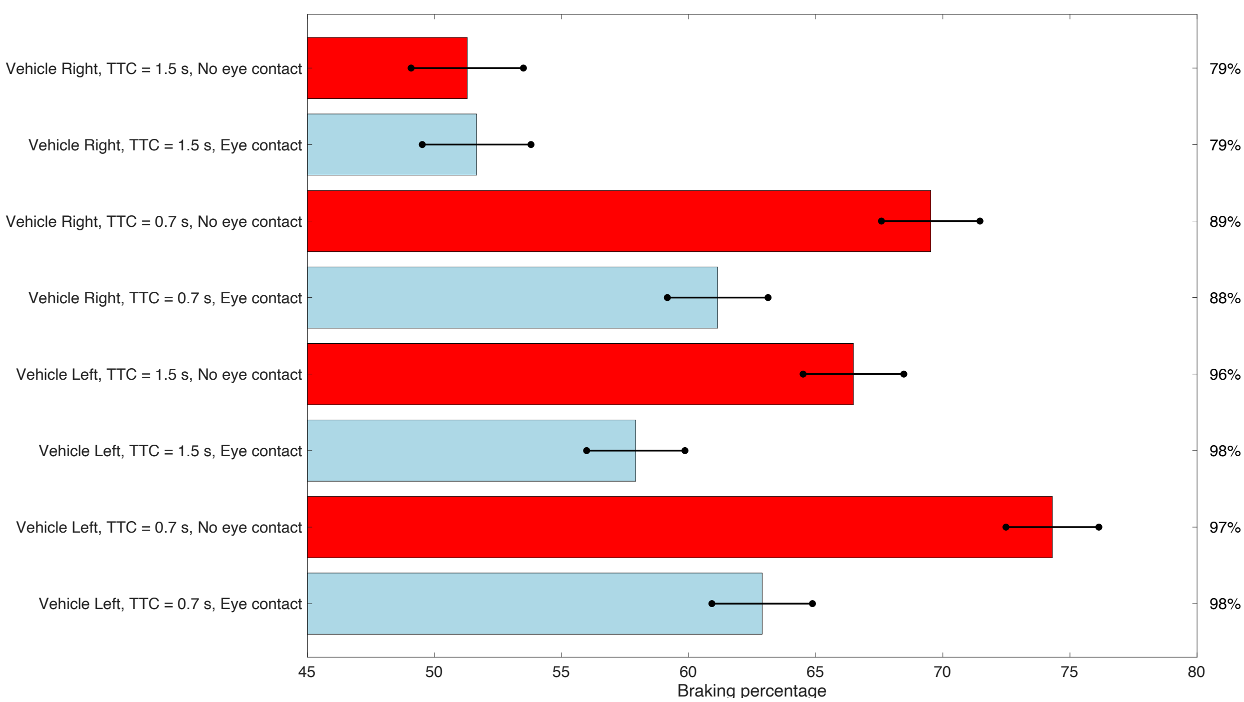


Figure 6. Braking percentage (n = 1086), as a function of driver eye-contact for four scenarios. The error bars represent within-subject confidence intervals (Morey, 2008). The numbers on the right represent the percentages of participants who reported 'True' to the statement "*A driver was visible in the car*" for these eight images.

Discussion

This work aimed to investigate the extent to which the appearance of an approaching vehicle influences cyclists' decision-making behaviour. We based our experiment on the design of Vlakveld et al. (2020). In addition to the value of replication offered by the current paper, this study offers insights on the effects of blinded windows, eye contact, the visual complexity of the surroundings on decision-making, and response times. Unlike Vlakveld et al. (2020), the current experiment was conducted with images instead of video clips, combined with introductory videos based on which participants could get an impression of the speed of the vehicle and cyclist. The static stimuli allowed us to make tightly controlled comparisons.

Replication of Vlakveld et al. (2020)

Our effects resemble those of Vlakveld et al. (2020). That is, the more urgent the situation, the more likely the cyclists were to brake, and the vehicle with eHMI (Automated GO) encouraged the cyclists to continue pedalling. The effect of urgency was stronger than in Vlakveld et al., indicating that our image-based method is sensitive. More specifically, in Experiment 1 of our study, participants showed 15–31% increases in the braking percentages between TTC = 1.5 s and TTC = 0.7 s, whereas, in Vlakveld et al., the increases between TTC = 1.7 s and TTC = 0.7 s were only 4–9%. Overall braking percentages were different as well (between 49 and 81% in Experiment 1 of our study versus between 22% and 47% in Vlakveld et al.) A possible cause for the difference is that participants in Vlakveld et al. were Dutch, and hence more familiar with the fact that the cyclists had right of way (but see Figures S2 and S3 showing strong cross-national similarity of effects in Experiments 1 and 2).

In Experiment 2, which aimed to determine which AV features were observable and memorable, the effects of urgency on cyclists brake/continue decision-making were smaller compared to Experiment 1. A possible explanation is that participants in Experiment 2 used more time to reflect on the AV features (response times were about four times as long in Experiment 2 compared to Experiment 1), rendering the effect of urgency less relevant. On top of this, since the participants in Experiment 2 were asked the same questions after each image, it is likely that they knew what features to look for. It may be more difficult to detect the AV's features in a short time frame in real traffic, although this may depend on the AV's speed, distance, and approach direction.

In summary, the direction of the effects of urgency and the presence of an eHMI as reported in the video clip study by Vlakveld et al. were found to be generalisable towards a cross-national image-based study. However, a difference between the findings of our study and the findings of Vlakveld et al. (2020) is that in the latter, the participants were more likely to brake for the automated vehicle (i.e., without the GO eHMI) than for a traditional vehicle, whereas, in our study, no significant difference between these two conditions was observed. Our findings are in line with a simulator study by TRL (2017), which reported that AV distinguishability via lidar on the roof had no significant effect on gap acceptance, a video-based experiment by Dey et al. (2019), which concluded that knowledge of a vehicle driving mode does not play a significant role in pedestrians' road-crossing behaviours, and a study using video images presented in a head-mounted display which found that vehicle type did not have a significant impact on cyclists' crossing intentions (Nuñez Velasco et al., 2020). A possible reason for the lack of effect is that stickers and lidar are relatively hard to detect, as our Experiment 2 showed. Furthermore, although Experiment 2 showed that the driver's presence was well noticed, it may have been hard for participants to distinguish whether the driver was attentive (driver looking forward in the traditional vehicle) or inattentive (driven looking downward in the AV). As pointed out above, Vlakveld et al. used video clips, whereas we used still images. It is possible that certain features, such as the rotating lidar on top of the AV, stood out in Vlakveld et al.'s study and may have caused some participants to brake in their study.

Novel findings

Besides replicating Vlakveld et al. (2020), our study was concerned with examining several effects not described by Vlakveld et al. First, the visual complexity of the surroundings had negligible effects on cyclists's decision-making. An eye-tracking study by Lappi et al. (2017) similarly showed that drivers make very few fixations on irrelevant stimuli. Previous research has cautioned that eHMIs might contribute to additional cognitive load (Dey et al., 2020; Moore et al., 2019). The present study suggests that participants are able to ignore irrelevant information and that the effectiveness of an eHMI is independent of whether one cycles in a rural environment or a more built-up environment. Future research may test other forms of scene complexity, such as complexity defined as the number of road users in the traffic scene.

Second, we found that if a traditional vehicle (Experiments 1 & 2) or an AV (Experiment 2) had blinded windows, participants were more likely to brake and responded faster compared to a traditional vehicle with a visible driver. These effects may be related to the notion that vehicles with blinded/tinted windows are associated with more antisocial and dangerous driving behaviour than vehicles where the driver is visible (Hennessy et al., 2004). Furthermore, the blinded windows were easy to recognise, with correct detection rates of 83–92% in Experiment 2. In summary, it seems that blinded windows are a deterrent.

Third, the absence of a driver caused cyclists to brake (Experiment 2), except when the eHMI 'GO' was present. In fact, in Experiment 1, the eHMI seemed to work better (i.e., cyclists were more likely to continue pedalling) when the driver was absent as compared to when a driver was present. This latter effect may be explained by the notion that a person behind the steering wheel could create the impression of this person being in control. That is, if a driver sits behind the wheel, it may be unclear to other road users whether the AV is eHMI signal is to trusted, as there may be a 'risk' that the car is being driven manually or that the driver in the car will override the eHMI signal. It is noted, however, that these interactive effects, although statistically significant, are not robust since they were not consistent between Experiments 1 and 2 (Figure 3 vs. 5). That is, the effect of the absence of a driver seems contingent on subtleties such as whether participants take the time to deliberate on the image (Experiment 2) or not (Experiment 1).

Fourth, we found that eye contact promotes the cyclist to continue pedalling. Our results provide some justification for a study performed by Chang et al. (2017), which presented an eHMI consisting of artificial eyes at the location of the headlamps. They found that synthetic 'eye contact' established by the eHMI led to faster correct crossing decisions and generated a safer feeling to cross the road. The effect of eye-contact in Experiment 2 was contingent on driver visibility. Research by AlAdawy et al. (2019) indicates that in most cases, pedestrians begin crossing before the driver's face or gaze can be distinguished through the windshield. Similarly, it has to be determined whether the present findings generalise to real traffic, where factors such as windshield glare may affect the visibility of the driver.

A recent study by Faas et al. (2021), which appeared online after we published our preprint, appears to confirm our findings using a Wizard-of-Oz method. More specifically, they concluded that "*without an eHMI, pedestrians felt significantly less safe if the windshield was tinted or the driver was distracted as compared to an attentive driver*" (p. 1364). This corresponds to Figure 5, in which we showed that the No Driver and Blinded conditions made cyclists brake, especially if there was no eHMI (i.e., Automated and Traditional vehicle types).

Limitations

In this study, participants were presented with only two conflict types (Vehicle Left, Vehicle Right). In real traffic, vehicles can come from different sides, which could affect the results. For example, in a previous online study where the cyclist was in the AV's blind spot, it was found that 'self-driving' stickers on the AV increased the cyclists' confidence that the AV had noticed them compared to baseline (Rodríguez Palmeiro et al., 2018), which may be because AVs are expected to have an omnidirectional vision. Future research should include a larger variety of scenarios and response options (i.e., not only braking or pedalling, but also steering and different levels of speed). Another limitation is that participants were unlikely to have experience with AVs and eHMIs, and long-term effects are therefore unknown (see Cefkin et al., 2019, for a discussion). As pointed out by TRL (2017), "*drivers typically do not feel sufficiently knowledgeable about AV behaviour to treat them any differently than they would an HDV [Human Driven Vehicle]*" (p. 5).

Another point of attention is that our study was conducted with an international sample, to a large extent represented by people from Venezuela, the USA, and Russia. Earlier online research has shown that participants from different countries are sensitive to different types of traffic risks (Bazilinskyy et al., 2020b). Similarly, at Amazon Mechanical Turk, people from India are overrepresented (Ross et al., 2010). It would have been possible to apply a selection and only admit participants from Western Europe (see Kovácsová et al., 2019), so that the participants are more familiar with the context and traffic rules of the images from our study (e.g., shark teeth indicating right of way). Still, our regression analysis for participants from different countries separately revealed fairly consistent baseline braking values ('constant' in the regression analyses) and consistent effects of urgency between countries (see Figures S2 and S3 for Experiments 1 and 2, respectively). The consistency of effects may be because the perception of risk and physical proximity have a biological basis (Tresilian, 1999) and are less dependent on learned behaviour and knowledge, such as traffic rules.

Conclusions

In conclusion, this study replicated the effects of Vlakveld et al. (2020) regarding an eHMI 'GO' and temporal urgency. Furthermore, we found that the visual complexity of the surroundings has only minor effects on cyclists' decision-making. Finally, blinded windows cause cyclists to brake (unless an eHMI signals that the cyclists can go), and driver eye contact, if detectable, causes cyclists to continue pedalling. In other words, our findings suggest that future AVs, in which there is no longer an attentive or visible driver, may cause uncertainty among cyclists. Cyclists may benefit from an eHMI indicating the AV's intent.

Acknowledgement

This research is supported by grant 016.Vidi.178.047 (2018–2024; "*How should automated vehicles communicate with other road users?*"), which is financed by the Netherlands Organisation for Scientific Research (NWO).

Data Availability

The questionnaire used in Appen, image stimuli, video examples, anonymised data, and MATLAB code are accessible at https://www.dropbox.com/sh/y5klmou6lk83nw3/AACNzyt167EEApjguhr7cVwTa.

References

Ackermans, S., Dey, D., Ruijten, P., Cuijpers, R. H., & Pfleging, B. (2020). The effects of explicit intention communication, conspicuous sensors, and pedestrian attitude in interactions with automated vehicles. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3313831.3376197

AlAdawy, D., Glazer, M., Terwilliger, J., Schmidt, H., Domeyer, J., Mehler, B., Reimer, B., & Fridman, L. (2019). Eye contact between pedestrians and drivers. *Proceedings of the Tenth International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design* (pp. 301–307). Santa Fe, New Mexico.

Barcikowski, R. S. (1981). Statistical power with group mean as the unit of analysis. *Journal of Educational Statistics, 6*, 267–285. https://doi.org/10.3102%2F10769986006003267

Bazilinskyy, P., Dodou, D., & De Winter, J. C. F. (2020a). External human-machine interfaces: Which of 729 colors is best for signaling 'Please (do not) cross'? *IEEE International Conference on Systems, Man and Cybernetics (SMC)* (pp. 3721–3728). Toronto, Canada. https://doi.org/10.1109/SMC42975.2020.9282998

Bazilinskyy, P., Eisma, Y. B., Dodou, D., & De Winter, J. C. F. (2020b). Risk perception: A study using dashcam videos and participants from different world regions. *Traffic Injury Prevention*, *21*, 347–353. https://doi.org/10.1080/15389588.2020.1762871

Bazilinskyy, P., Kooijman, L., Dodou, D., & De Winter, J. C. F. (2021). How should external Human-Machine Interfaces behave? Examining the effects of colour, position, message, activation distance, vehicle yielding, and visual distraction among 1,434 participants. *Applied Ergonomics, 95*, 103450. https://doi.org/10.1016/j.apergo.2021.103450

Brown, L. D., Cai, T. T., & DasGupta, A. (2001). Interval estimation for a binomial proportion. Statistical Science, 16, 101–133. https://doi.org/10.1214/ss/1009213286

Cefkin, M., Zhang, J., Stayton, E., & Vinkhuyzen, E. (2019). Multi-methods research to examine external HMI for highly automated vehicles. *International Conference on Human-Computer Interaction* (pp. 46–64). Springer, Cham. https://doi.org/10.1007/978-3-030-22666-4_4

Chang, C. M., Toda, K., Sakamoto, D., & Igarashi, T. (2017). Eyes on a car: an interface design for communication between an autonomous car and a pedestrian. *Proceedings of the 9th International Conference on Automotive User Interfaces and Interactive Vehicular Applications* (pp. 65–73). Oldenburg, Germany. https://doi.org/10.1145/3122986.3122989

Chen, W., Jiang, Q., Zhuang, X., & Ma, G. (2020). Comparison of pedestrians' gap acceptance behavior towards automated and human-driven vehicles. In D. Harris & W. C. Li (Eds.), *Engineering Psychology and Cognitive Ergonomics. Cognition and Design. HCII 2020. Lecture Notes in Computer Science, vol 12187* (pp. 253–261). Cham: Springer. https://doi.org/10.1007/978-3-030-49183-3_20

Clamann, M., Aubert, M., & Cummings, M. L. (2017). Evaluation of vehicle-to-pedestrian communication displays for autonomous vehicles. *Transportation Research Board 96th Annual Meeting*, 17-02119.

Continental. (2019). Continental enhances intelligent glass control. https://www.continental.com/en/press/press-releases/2019-07-25-intelligent-glass-control-179950

Deb, S., Hudson, C. R., Carruth, D. W., & Frey, D. (2018a). Pedestrians receptivity in autonomous vehicles: Exploring a video-based assessment. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *62*, 2061–2065. https://doi.org/10.1177/1541931218621465

Deb, S., Rahman, M. M., Strawderman, L. J., & Garrison, T. M. (2018b). Pedestrians' receptivity toward fully automated vehicles: Research review and roadmap for future research. *IEEE Transactions on Human-Machine Systems*, *48*, 279–290. https://doi.org/10.1109/THMS.2018.2799523

Deb, S., Warner, B., Poudel, S., & Bhandari, S. (2016). Identification of external design preferences in autonomous vehicles. In H. Yang, Z. Kong, & M. D. Sarder (Eds.), *Proceedings of the 2016 Industrial and Systems Engineering Research Conference* (pp. 69–44). Anaheim, CA.

De Clercq, G. K., Dietrich, A., Núñez Velasco, P., De Winter, J. C. F., & Happee, R. (2019). External human-machine interfaces on automated vehicles: Effects on pedestrian crossing decisions. *Human Factors*, *61*, 1353–1370. https://doi.org/10.1177/0018720819836343

De Leeuw, J. R. (2015). jsPsych: A JavaScript library for creating behavioral experiments in a Web browser. *Behavior Research Methods*, *47*, 1–12. https://doi.org/10.3758/s13428-014-0458-y

Dey, D., Habibovic, A., Löcken, A., Wintersberger, P., Pfleging, B., Riener, A., Martens, M., & Terken, J. (2020). Taming the eHMI jungle: A classification taxonomy to guide, compare, and assess the design principles of automated vehicles' external human-machine interfaces. *Transportation Research Interdisciplinary Perspectives, 7*, 100174. https://doi.org/10.1016/j.trip.2020.100174

Dey, D., Martens, M., Eggen, B., & Terken, J. (2019). Pedestrian road-crossing willingness as a function of vehicle automation, external appearance, and driving behaviour. *Transportation Research Part F: Traffic Psychology and Behaviour*, *65*, 191–205. https://doi.org/10.1016/j.trf.2019.07.027

Dietrich, A., Tondera, M., & Bengler, K. (2020). Automated vehicles in urban traffic: the effect of kinematics and eHMIs on pedestrian crossing behavior. *Advances in Transportation Studies*, *2020*, 73–84.

Eisma, Y. B., Van Bergen, S., Ter Brake, S. M., Hensen, M. T. T., Tempelaar, W. J., & De Winter, J. C. F. (2020). External human-machine interfaces: The effect of display location on crossing intentions and eye movements. *Information, 11*, 13. https://doi.org/10.3390/info11010013

European Commission. (2015). Road safety in the European Union: Trends, statistics and main challenges. https://ec.europa.eu/transport/sites/transport/files/road_safety/pdf/vademecum_2015.pdf

Faas, S. M., Mathis, L. A., & Baumann, M. (2020). External HMI for self-driving vehicles: which information shall be displayed? *Transportation Research Part F: Traffic Psychology and Behaviour*, *68*, 171–186. https://doi.org/10.1016/j.trf.2019.12.009

Faas, S. M., Stange, V., & Baumann, M. (2021). Self-driving vehicles and pedestrian interaction: Does an External human-machine interface mitigate the threat of a tinted windshield or a distracted driver? *International Journal of Human-Computer Interaction, 14*, 1364–1374. https://doi.org/10.1080/10447318.2021.1886483

Fridman, L., Mehler, B., Xia, L., Yang, Y., Facusse, L. Y., & Reimer, B. (2017). To walk or not to walk: Crowdsourced assessment of external vehicle-to-pedestrian displays. https://arxiv.org/pdf/1707.02698.pdf

Habibovic, A., & Davidsson, J. (2012). Causation mechanisms in car-to-vulnerable road user crashes: Implications for active safety systems. *Accident Analysis & Prevention, 49*, 493–500. https://doi.org/10.1016/j.aap.2011.03.019

Habibovic, A., Lundgren, V. M., Andersson, J., Klingegård, M., Lagström, T., Sirkka, A., Fagerlönn, J., Edgren, C., Fredriksson, R., Krupenia, S., Saluäär, D., & Saluäär, D. (2018). Communicating intent of automated vehicles to pedestrians. *Frontiers in Psychology, 9*, 1336. https://doi.org/10.3389/fpsyg.2018.01336

Hennessy, D. A., Wiesenthal, D. L., Wickens, C., & Lustman, M. (2004). The impact of gender and stress on traffic aggressions: are we really that different? In J. P. Morgan (Ed.), *Focus on aggression research* (pp. 157–174). New York: Nova Science Publishers.

Hudson, C. R., Deb, S., Carruth, D. W., McGinley, J., & Frey, D. (2019). Pedestrian perception of autonomous vehicles with external interacting features. In I. Nunes (Ed.), *Advances in Human Factors and Systems Interaction. AHFE 2018. Advances in Intelligent Systems and Computing, 781*, 33–39. Cham: Springer. https://doi.org/10.1007/978-3-319-94334-3_5

Jayaraman, S. K., Creech, C., Tilbury, D. M., Yang, X. J., Pradhan, A. K., Tsui, K. M., & Robert, L. P. (2019). Pedestrian trust in automated vehicles: role of traffic signal and AV driving behavior. *Frontiers in Robotics and AI*, *6*, 117. https://doi.org/10.3389/frobt.2019.00117

Joisten, P., Alexandi, E., Drews, R., Klassen, L., Petersohn, P., Pick, A., Schwindt, S., & Abendroth, B. (2019). Displaying vehicle driving mode–Effects on pedestrian behavior and perceived safety. In T. Ahram, W. Karwowski, S. Pickl, & R. Taiar (Eds.), *Human Systems Engineering and Design II. IHSED 2019. Advances in Intelligent Systems and Computing, vol 1026*. Cham: Springer. https://doi.org/10.1007/978-3-030-27928-8_38

Jones, C. D., Kamei, I., Wilson, J. R., Mazuir, C., Raff, J., Dan, B., Kingman, D. E., & Melcher, M. (2020). *Systems with adjustable windows* (U.S. Patent No. 10,625,580). Washington, DC: U.S. Patent and Trademark Office.

Kaß, C., Schoch, S., Naujoks, F., Hergeth, S., Stemmler, T., Keinath, A., & Neukum, A. (2020). Using a bicycle simulator to examine the effects of external HMI on behavior of vulnerable interaction partners of automated vehicles. *Proceedings of Driving Simulation Conference 2020 Europe VR.* Antibes, France.

Kooijman, L., Happee, R., & De Winter, J. C. F. (2019). How do eHMIs affect pedestrians' crossing behavior? A study using a head-mounted display combined with a motion suit. *Information*, *10*, 386. https://doi.org/10.3390/info10120386

Kovácsová, N., De Winter, J. C. F., & Hagenzieker, M. P. (2019). What will the car driver do? A video-based questionnaire study on cyclists' anticipation during safety-critical situations. *Journal of Safety Research*, *69*, 11–21. https://doi.org/10.1016/j.jsr.2019.01.002

Lappi, O., Rinkkala, P., & Pekkanen, J. (2017). Systematic observation of an expert driver's gaze strategy—an on-road case study. *Frontiers in Psychology*, *8*, 620. https://doi.org/10.3389/fpsyg.2017.00620

Lekach, S. (2019). Why self-driving cars will need 'smart' windows. https://mashable.com/article/smart-glass-windows-self-driving-cars

Li, T., & Kockelman, K. M. (2016). Valuing the safety benefits of connected and automated vehicle technologies. *Transportation Research Board 95th Annual Meeting*, 16-1468.

Matsumura, K. (2017). A summary of laws for car window tint in three countries: US, UK and Japan. https://doi.org/10.5281/zenodo.556380

Matsumura, K., & Kirk, D. S. (2018). On active passengering: Supporting in-car experiences. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 1*, 1–23. https://doi.org/10.1145/3161176

Mercedes-Benz. (2015). The Mercedes-Benz F 015 luxury in motion. https://www.mercedes-benz.com/en/innovation/autonomous/research-vehicle-f-015-luxury-in-motion/?csref=sm_twr_gims2019_pc.html

Moore, D., Currano, R., Strack, G. E., & Sirkin, D. (2019). The case for implicit external human-machine interfaces for autonomous vehicles. *Proceedings of the 11th International Conference on Automotive User Interfaces and Interactive Vehicular Applications* (pp. 295–307). Utrecht, Netherlands. https://doi.org/10.1145/3342197.3345320

Morey, R. D. (2008). Confidence intervals from normalized data: A correction to Cousineau (2005). *Tutorial in Quantitative Methods for Psychology*, *4*, 61–64. https://doi.org/10.20982/tqmp.04.2.p061

Nuñez Velasco, J. P., De Vries, A., Farah, H., Van Arem, B., & Hagenzieker, M. (2020). Cyclists' crossing intentions when interacting with automated vehicles: A virtual reality study. *Information, 12*. https://doi.org/10.3390/info12010007

Räsänen, M., & Summala, H. (1998). Attention and expectation problems in bicycle–car collisions: an in-depth study. *Accident Analysis & Prevention, 35*, 657–666. https://doi.org/10.1016/S0001-4575(98)00007-4

Rodríguez Palmeiro, A., Van der Kint, S., Hagenzieker, M., Schagen, I., & De Winter, J. C. F. (2018). Cyclists' expectations when encountering automated vehicles: results of an international photo-based questionnaire. *Proceedings of the 7th International Cycling Safety Conference*. Barcelona, Spain.

Ross, J., Irani, L., Silberman, M. S., Zaldivar, A., & Tomlinson, B. (2010). Who are the crowdworkers? Shifting demographics in Mechanical Turk. *CHI'10 extended abstracts on Human Factors in Computing Systems* (pp. 2863–2872). https://doi.org/10.1145/3159652.3159661

SAE International. (2018). SAE Standards News: J3016 automated-driving graphic update. https://www.sae.org/news/2019/01/sae-updates-j3016-automated-driving-graphic

Schepers, J. P., Kroeze, P. A., Sweers, W., & Wüst, J. C. (2011). Road factors and bicycle–motor vehicle crashes at unsignalized priority intersections. *Accident Analysis & Prevention*, *43*, 853–861. https://doi.org/10.1016/j.aap.2010.11.005

Sen, G., & Sener, B. (2020). Design for Luxury Front-Seat Passenger Infotainment Systems with Experience Prototyping through VR. *International Journal of Human–Computer Interaction, 36*, 1714–1733. https://doi.org/10.1080/10447318.2020.1785150

Sundfør, H. B., Sagberg, F., & Høye, A. (2019). Inattention and distraction in fatal road crashes–results from in-depth crash investigations in Norway. *Accident Analysis & Prevention*, *125*, 152–157. https://doi.org/10.1016/j.aap.2019.02.004

SWOV. (2017). Fietsers [Cyclists] (Factsheet). https://www.swov.nl/feiten-cijfers/factsheet/fietsers

Tapiro, H., Oron-Gilad, T., & Parmet, Y. (2020). Pedestrian distraction: The effects of road environment complexity and age on pedestrian's visual attention and crossing behavior. *Journal of Safety Research*, *72*, 101–109. https://doi.org/10.1016/j.jsr.2019.12.003

Tresilian, J. R. (1999). Visually timed action: time-out for 'tau'? *Trends in Cognitive Sciences, 3*, 301–310. https://doi.org/10.1016/S1364-6613(99)01352-2

TRL. (2017). *Driver responses to encountering automated vehicles in an urban environment* (GATEway Project Report No. PPR807). https://trl.co.uk/Uploads/TRL/Documents/D4.6_Driver-responses-to-encountering-automated-vehicles-in-an-urban-environment_PPR807.pdf

Uber. (2020). Uber. https://www.uber.com/nl/nl/atg/technology

Vlakveld, W., Van der Kint, S., & Hagenzieker, M. P. (2020). Cyclists' intentions to yield for automated cars at intersections when they have right of way: Results of an experiment using high-quality video animations. *Transportation Research Part F: Traffic Psychology and Behaviour*, *71*, 288–307. https://doi.org/10.1016/j.trf.2020.04.012

Volvo. (2018). 360c. A new way to travel. https://www.volvocars.com/intl/cars/concepts/360c

Waymo. (2019). Waymo. https://waymo.com

Supplementary Material

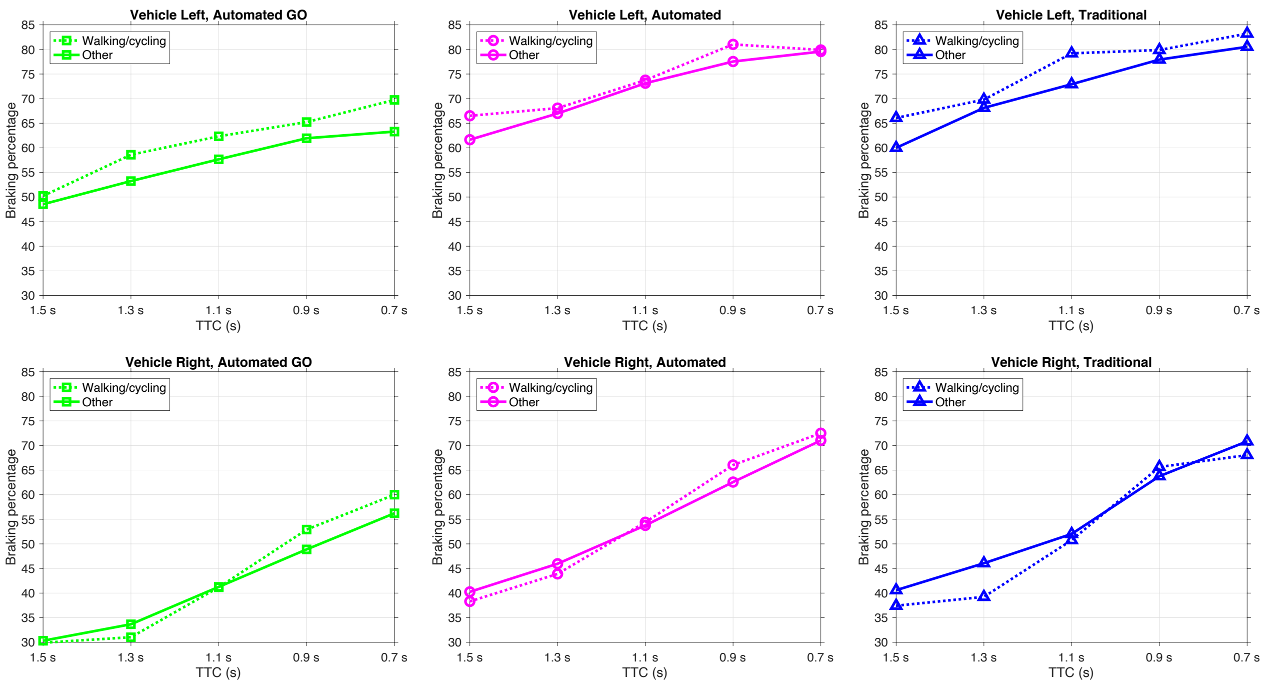


Figure S1. Experiment 1: Braking percentage, as a function of conflict type (Vehicle Left vs. Vehicle Right), urgency level (1.5 s = low urgency, 0.7 s = high urgency), and vehicle type (Automated GO, Automated, Traditional). A distinction is made between participants whose primary self-reported mode of transport was "Walking/Cycling" (*n* = 126) versus other participants ("Private vehicle", "Public transportation", "Motorcycle", "Other", or "I prefer not to respond") (*n* = 1134).

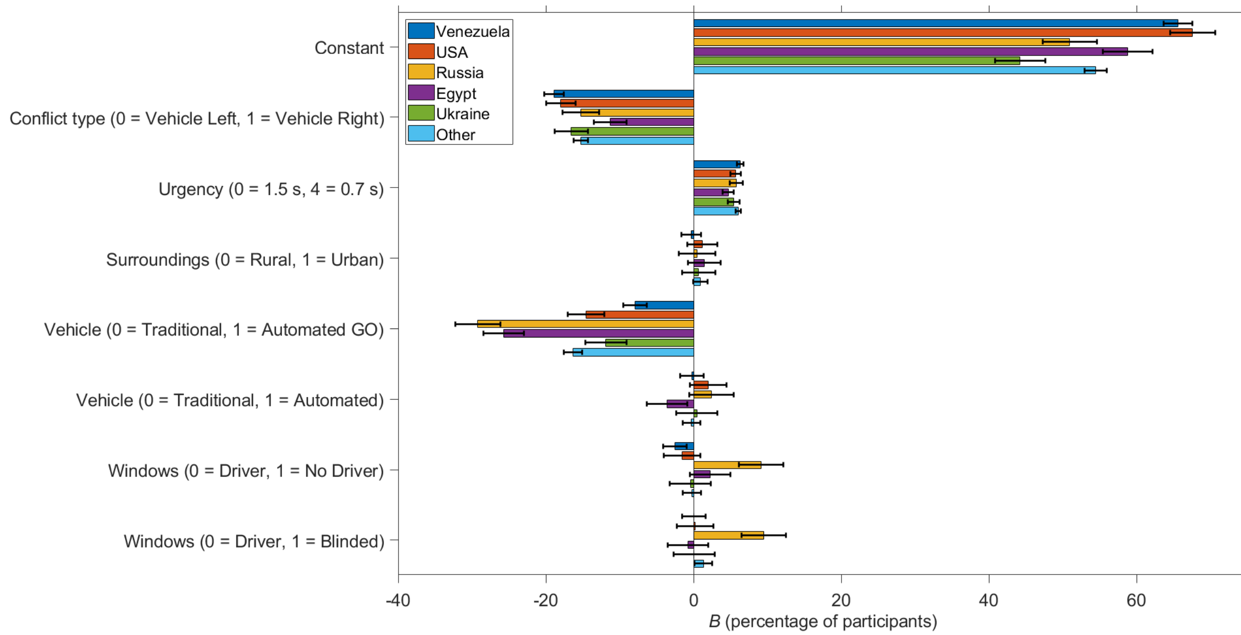


Figure S2. Experiment 1: Regression coefficients for prediction of the braking percentage, at the level of images (n = 180), for the five countries with the largest number of participants, and for the remainder of the countries. Error bars represent 95% confidence intervals.

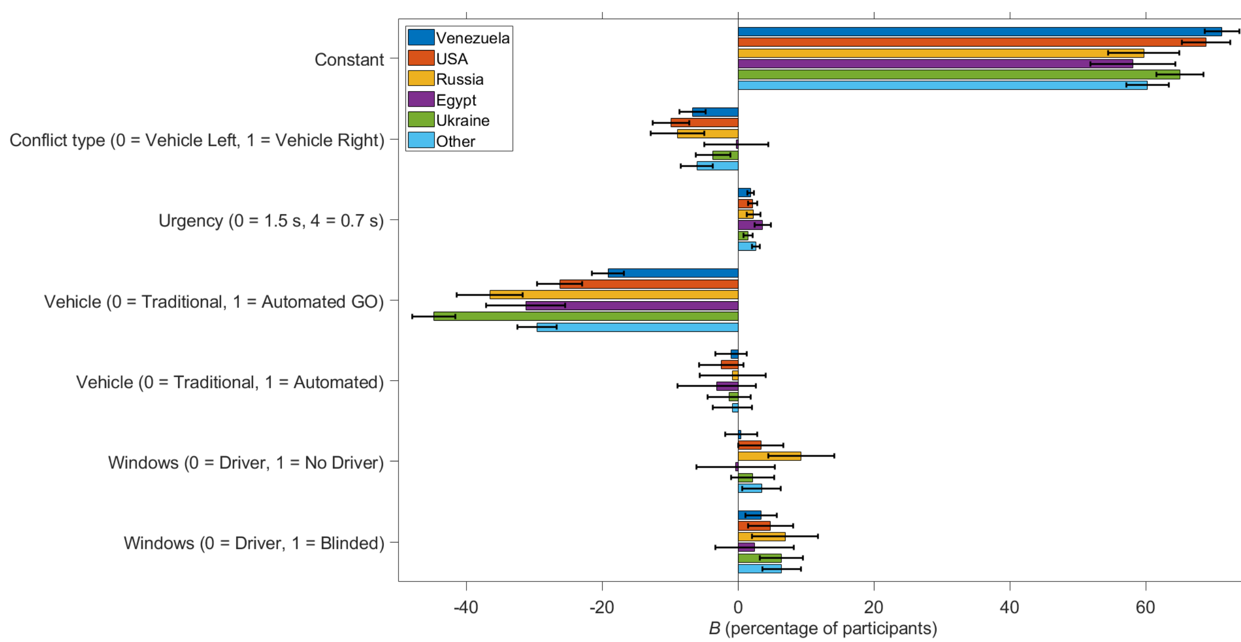


Figure S3. Experiment 2: Regression coefficients for prediction of the braking percentage, at the level of images (n = 36 images without eye contact), for the five countries with the largest number of participants in Experiment 1, and for the remainder of the countries. Error bars represent 95% confidence intervals.

Table S1.
Experiment 2: Regression model statistics for prediction of the braking percentage (n = 36 images without eye contact).

Predictor	**B**	**β**	***t***	***p***

Constant	65.533			
Conflict (0 = Vehicle Left, 1 = Vehicle Right)	-6.384	-0.237	-7.114	<0.001
Urgency (0 = 1.5 s, 4 = 0.7 s)	2.263	0.336	10.087	<0.001
Visual complexity (0 = Rural, 1 = Urban)	—	—	—	—
Vehicle (0 = Traditional, 1 = Automated GO)	-25.709	-0.899	-23.392	<0.001
Vehicle (0 = Traditional, 1 = Automated)	-1.042	-0.036	-0.948	0.351
Windows (0 = Driver, 1 = No Driver)	2.266	0.079	2.062	0.048
Windows (0 = Driver, 1 = Blinded)	4.978	0.174	4.530	<0.001

$F(6,29) = 145.7$, $p < 0.001$, $r = 0.984$, $r^2 = 0.968$.

Table S2.

Experiment 2: Regression model statistics for prediction of the median response time in milliseconds (n = 36 images without eye contact).

Predictor	***B***	**β**	***t***	***p***
Constant	5381.2			
Conflict (0 = Vehicle Left, 1 = Vehicle Right)	-112.9	-0.102	-1.172	0.251
Urgency (0 = 1.5 s, 4 = 0.7 s)	-2.3	-0.008	-0.095	0.925
Visual complexity (0 = Rural, 1 = Urban)	—	—	—	—
Vehicle (0 = Traditional, 1 = Automated GO)	192.9	0.164	1.635	0.113
Vehicle (0 = Traditional, 1 = Automated)	800.9	0.682	6.788	<0.001
Windows (0 = Driver, 1 = No Driver)	291.8	0.248	2.473	0.020
Windows (0 = Driver, 1 = Blinded)	-543.2	-0.462	-4.604	<0.001

$F(6,29) = 17.20$, $p < 0.001$, $r = 0.884$, $r^2 = 0.781$.

Table S3.

Experiment 2: Overview of the 40 images and results (braking percentage, median response time, and percentage of participants indicating 'true' for four image features).

Image No	Conflict type (1: Vehicle Right, 2: Vehicle Left)	Frame level (1: TTC = 1.5 s, 5: TTC = 0.7 s)	Background (1: Rural, 2: Urban)	Car (1: Automated GO, 2: Automated, 3: Traditional)	Window (1: Driver, 2: No Driver, 3: Blinded)	Eye contact (0: No, 1: Yes)	Indicator (0: Off, 1: On)	Braking percentage	Median response time (ms)	There was a sticker and sensor on the car	The windows of the car were blinded	There was a message 'GO' on the car	A driver was visible in the car
1	1	1	2	1	1	0	0	36%	5625	49%	17%	82%	70%
2	1	1	2	1	2	0	0	37%	5562	50%	17%	81%	16%
3	1	1	2	1	3	0	0	39%	4861	49%	84%	82%	6%
4	1	1	2	2	1	0	0	56%	6249	42%	15%	7%	73%
5	1	1	2	2	2	0	0	59%	6170	45%	16%	6%	12%
6	1	1	2	2	3	0	0	61%	5294	43%	83%	6%	6%
7	1	1	2	3	1	0	0	51%	5124	7%	14%	4%	79%
8	1	1	2	3	1	1	0	52%	5055	5%	13%	4%	79%
9	1	1	2	3	2	0	0	57%	5856	5%	17%	3%	15%
10	1	1	2	3	3	0	0	62%	4628	5%	84%	3%	5%
11	1	5	2	1	1	0	1	46%	5344	57%	14%	85%	85%
12	1	5	2	1	2	0	1	45%	5477	57%	17%	84%	11%
13	1	5	2	1	3	0	1	47%	5037	55%	85%	84%	6%
14	1	5	2	2	1	0	1	68%	6112	54%	12%	8%	90%
15	1	5	2	2	2	0	1	72%	6360	55%	15%	8%	10%
16	1	5	2	2	3	0	1	74%	5529	53%	86%	7%	5%
17	1	5	2	3	1	1	1	61%	5216	9%	13%	3%	88%
18	1	5	2	3	1	0	1	70%	4878	8%	12%	4%	89%
19	1	5	2	3	2	0	1	73%	6394	9%	21%	5%	10%
20	1	5	2	3	3	0	1	76%	4770	9%	86%	3%	5%
21	2	1	2	1	1	0	0	43%	5724	71%	15%	87%	56%
22	2	1	2	1	2	0	0	43%	5884	73%	16%	86%	13%
23	2	1	2	1	3	0	0	45%	5210	68%	87%	87%	7%
24	2	1	2	2	1	0	0	67%	6370	70%	14%	20%	55%
25	2	1	2	2	2	0	0	67%	6274	69%	15%	21%	12%
26	2	1	2	2	3	0	0	71%	5512	66%	90%	18%	5%
27	2	1	2	3	1	0	0	66%	5355	12%	10%	4%	96%
28	2	1	2	3	1	1	0	58%	5537	12%	10%	4%	98%
29	2	1	2	3	2	0	0	70%	6080	12%	15%	5%	11%
30	2	1	2	3	3	0	0	74%	4591	6%	92%	3%	6%
31	2	5	2	1	1	0	0	46%	5693	73%	14%	91%	84%
32	2	5	2	1	2	0	0	47%	5375	72%	15%	90%	10%
33	2	5	2	1	3	0	0	50%	5359	72%	90%	91%	5%
34	2	5	2	2	1	0	0	72%	6423	69%	12%	21%	85%
35	2	5	2	2	2	0	0	75%	6242	71%	13%	19%	8%
36	2	5	2	2	3	0	0	77%	5913	66%	90%	19%	5%
37	2	5	2	3	1	1	0	63%	4836	6%	10%	4%	98%
38	2	5	2	3	1	0	0	74%	4990	5%	9%	3%	97%
39	2	5	2	3	2	0	0	77%	5645	6%	11%	3%	9%
40	2	5	2	3	3	0	0	80%	4595	6%	92%	3%	5%

Note. The cells are linearly filled based on their value.