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Safety Assessment of the Interaction Between an Automated Vehicle and a Cyclist: A Controlled Field Test

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Abstract

The operation of automated vehicles (AVs) on shared roads requires attention concerning their interactions with vulnerable road users (VRUs), such as cyclists. This study investigates the safety of cyclists when they interact with an AV and compares it with their interaction with a conventional vehicle. Overall, 29 cyclists participated in a controlled field experiment consisting of interaction scenarios in which a vehicle approached the cyclist from behind. Four interaction scenarios were included: manual and automated following and manual and automated overtaking of the cyclist. The vehicle operated in all scenarios in a manual mode for safety reasons. However, before each ride, participants received information about the vehicle's operation mode (automated or manual). The following attributes were considered: overtaking speed, overtaking lateral distance, following distance, and roadside objects. The objective and the subjective risks were evaluated in each scenario. The objective risk was assessed using the probabilistic driving risk field, and the subjective risk was assessed based on the cyclists' self-reported risk values, cycling behavior, and their trust in AVs. The results show that automated and manual following have similar objective and subjective risks, while automated overtaking has a higher level of objective and subjective risks than manual overtaking. The results also show that a longer interaction time leads to an increase in cycling speed and a decrease in the lateral distance of the cyclist to the curb. Thus, we conclude that automated following is a safer option for short traveling distances, while for longer traveling distances, manual overtaking is preferred. Additionally, a short lateral distance from the cyclist when overtaking increases the subjective and objective risks.

Keywords

pedestrians, bicycles, human factors, safety, advanced driver assistance systems, safety, modeling and forecasting

The operation of automated vehicles (AVs) on shared roads is expected to result in frequent interactions with other road users. These road users mostly use implicit communication channels (*1*), which AVs do not yet fully recognize. To prevent misunderstanding in communication between AVs and cyclists, some current AVs are programmed to follow the cyclist at the rider speed (*2*). Such a behavioral approach is not efficient for traffic operation performance. Also, cyclists might feel unsafe when being followed by a vehicle (*3*). Therefore, programming the interactions with vulnerable road users (VRUs), such as pedestrians and cyclists, requires special attention in AV motion control.

Previous field test studies investigating the interactions between AVs and VRUs mainly focused on the interactions of AVs with pedestrians. Several studies show that pedestrians generally reported feeling less safe and behaved more cautiously when interacting with AVs (*1*, *4–7*). It was also found that the most influencing factors are the speed of the vehicle and its distance to the pedestrian (*8–12*). There are very few studies focusing on the interactions between cyclists and AVs, and there are

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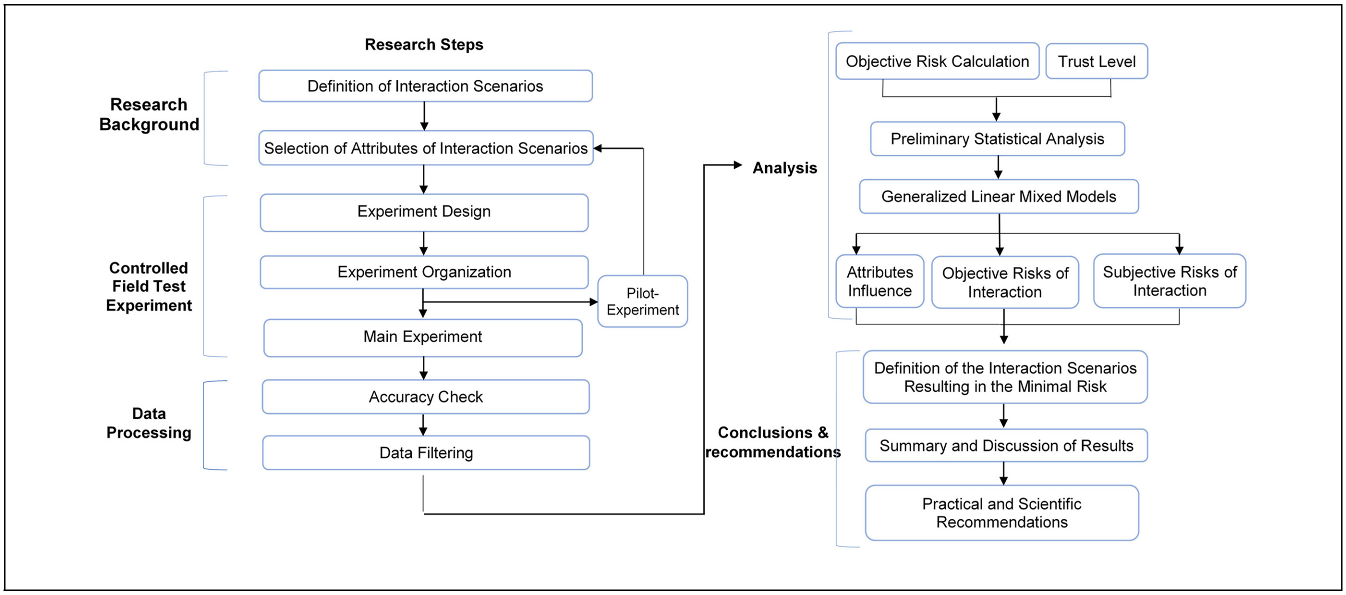

Figure 1. Research steps.

no studies in the literature, to the best of our knowledge, that focus on AVs' interactions with cyclists based on field tests. Rodríguez Palmeiro et al. (*10*) conducted a photo experiment study. The purpose was to investigate if cyclists' expectations and behavioral intentions would differ when interacting with AVs compared with interacting with manually driven vehicles. The researchers found that the participants were not confident that AVs would notice them (*13*). Nuñez Velasco et al. (*14*) used a virtual reality method to determine the main factors influencing cyclists' intentions to cross when interacting with an AV as compared with a conventional vehicle. The results showed that the gap size and right of way were the primary factors affecting the crossing intentions of cyclists, while the vehicle type (AV versus conventional vehicle) and vehicle speed did not have a significant effect on the crossing intentions.

In addition to the operational mode of the vehicle (automated or manual), the characteristics of the cyclist and the road environment could also affect these interactions. Several studies, such as Llorca et al. (*12*), Rubie et al. (*15*), Beck (*16*), and Rasch et al. (*17*) have shown that cyclists' subjective risk is influenced by the lateral distance when a vehicle passes a cyclist, and also the speed and the size of the overtaking vehicle. Chuang et al. (*18*) found that a longer passing time influences the observed increase in steering wheel angle and speed of the cyclist. Studies also show that the gender of a cyclist affects the distance of overtaking. Drivers of conventional cars prefer to keep more distance from female cyclists than from male cyclists, according to Chuang et al. (*18*), and likewise if the cyclist appears to be female (*19*).

The literature review highlights a gap in the knowledge about cyclists' behavior when interacting with AVs. To minimize the risk when AVs interact with cyclists, investigating the subjective and objective risks of different maneuvers and driving modes of AVs during these interactions is required. It is also essential to investigate the potential changes in the behavior (i.e., behavioral adaptation) of cyclists depending on the type of vehicle they are interacting with (manual versus automated) and the duration of the interaction. Therefore, the main research question of this study is: Which interaction scenario minimizes the subjective and objective risks when an AV approaches a cyclist from behind?

Research Methodology

This section is structured as follows. First, the controlled field test setup is explained, followed by the data collection method, the experiment procedure, and the analysis method. The research steps are further detailed in Figure 1.

This study analyzed the behavior of participants who were riding an instrumented bicycle while they were followed or passed by a vehicle. The participants were informed that the vehicle would be operated in manual or automated mode (while the vehicle was always operated in manual mode).

Controlled Field Experiment

This sub-section describes the field test location, recruitment of participants, the experiment instrumentation, and the interaction scenarios.

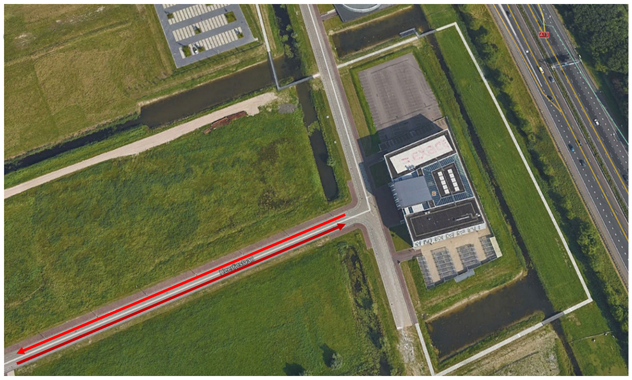

Figure 2. Controlled field test location from Google Earth (51° 59'23.29" N 4° 23'15.70" E).

Field Test Location. The experiment took place on a quiet minor street located at the Delft University of Technology campus at Heertjeslaan. The straight road section of 200 m in length consists of one lane per direction for driving cars and two bicycle lanes (see Figure 2). The complete street was closed to any other traffic during the experiment.

Participants. Twenty-five participants (13 males and 12 females) from the same age group (mean = 25.4 years; standard deviation = 1.3 years) took part in the experiment. Only participants who had experience in cycling were invited to the experiment.

Experiment Instrumentation. An equipped bicycle and an equipped vehicle were used for the experiment (see Figure 3).

The bicycle was equipped with three-point LIDAR, two cameras, GPS, and an accelerometer. A Toyota Prius vehicle was instrumented with a GPS, an accelerometer, and a video camera. The LIDAR and GPS collected data at a resolution of five measurements per second.

Each participant completed a questionnaire on their personal characteristics and their basic trust in technologies. Trust in technology was assessed using a questionnaire developed by Körber (*20*). The questionnaire has four underlying dimensions: reliability and propensity to trust, predictability, familiarity, and trust in automation. Answers on each of the 19 questions were collected with a Likert scale ranging from 1 "strongly disagree" to 5 "strongly agree."

After each interaction, the participants were also asked about their level of experienced risk (i.e., subjective risk). The subjective risk level was self-reported on a scale of 100 degrees, with steps of five degrees and with higher scores representing a higher risk level.

Scenarios. The controlled field test concerns a situation where the vehicle is approaching the cyclist from behind. In such a case, two sub-scenarios emerge: the first is when the vehicle continues to follow the cyclist, and the second is when the vehicle overtakes the cyclist. As mentioned in the literature (*3–7*), pedestrians generally reported feeling less safe and behaved more cautiously when interacting with AVs, thus this research aimed to investigate the behavioral adaptation of cyclists when interacting with an AV compared with interacting with a conventional vehicle. Thus, the study included four scenarios: automated following, automated overtaking, manual following, and manual overtaking. The order of rides for cyclists was counterbalanced. A sticker with the words "self-driving" was placed on the side of the vehicle in scenarios with automated mode. In practice, in all scenarios, the vehicle operated in a manual mode for safety reasons. However, before each ride, the participants received information about the vehicle's operation mode (automated/manual). At the end of each ride, the participants were asked whether they interacted with an AV or a manual vehicle. Even though the participants received this information explicitly at the start, it was still necessary to check whether the participants believed that they interacted with an AV. In two instances, the participants mentioned that the vehicle was operated in an automated mode when they were told before the ride that the vehicle would operate in a manual mode. Therefore, we analyzed the data from these two rides as automated driving mode data, as it is important to consider what the cyclists thought. In addition to the operation mode of the vehicle (automated or manual) and the exact type of maneuver (following or overtaking), the study considered the characteristics of the AV driving behavior, the features of the cyclist (gender and age), and the road environment based on insights from previous studies. Therefore, the following attributes were considered: overtaking lateral distance (1.5 m; 3.5 m, correspondingly related to the narrow street and wide street overtaking scenarios), overtaking vehicle speed (cyclist speed + 5 km/h; cyclist speed + 10 km/h), and type of right-hand side objects (curb with a brick-paved surface; curb with grass, see Figure 4). During the overtaking maneuver, the vehicle followed the participant for 20 s and then proceeded to overtake the cyclist at the specified lateral distance in that scenario (1.5 m; 3.5 m). The driver was instructed to keep the predefined distance (1.5 m; 3.5 m); two white lines were drawn on the carriageway to help drivers navigate. Cyclists had the freedom to adjust their distance to the vehicle. The following distance was always 3 m behind the cyclist.

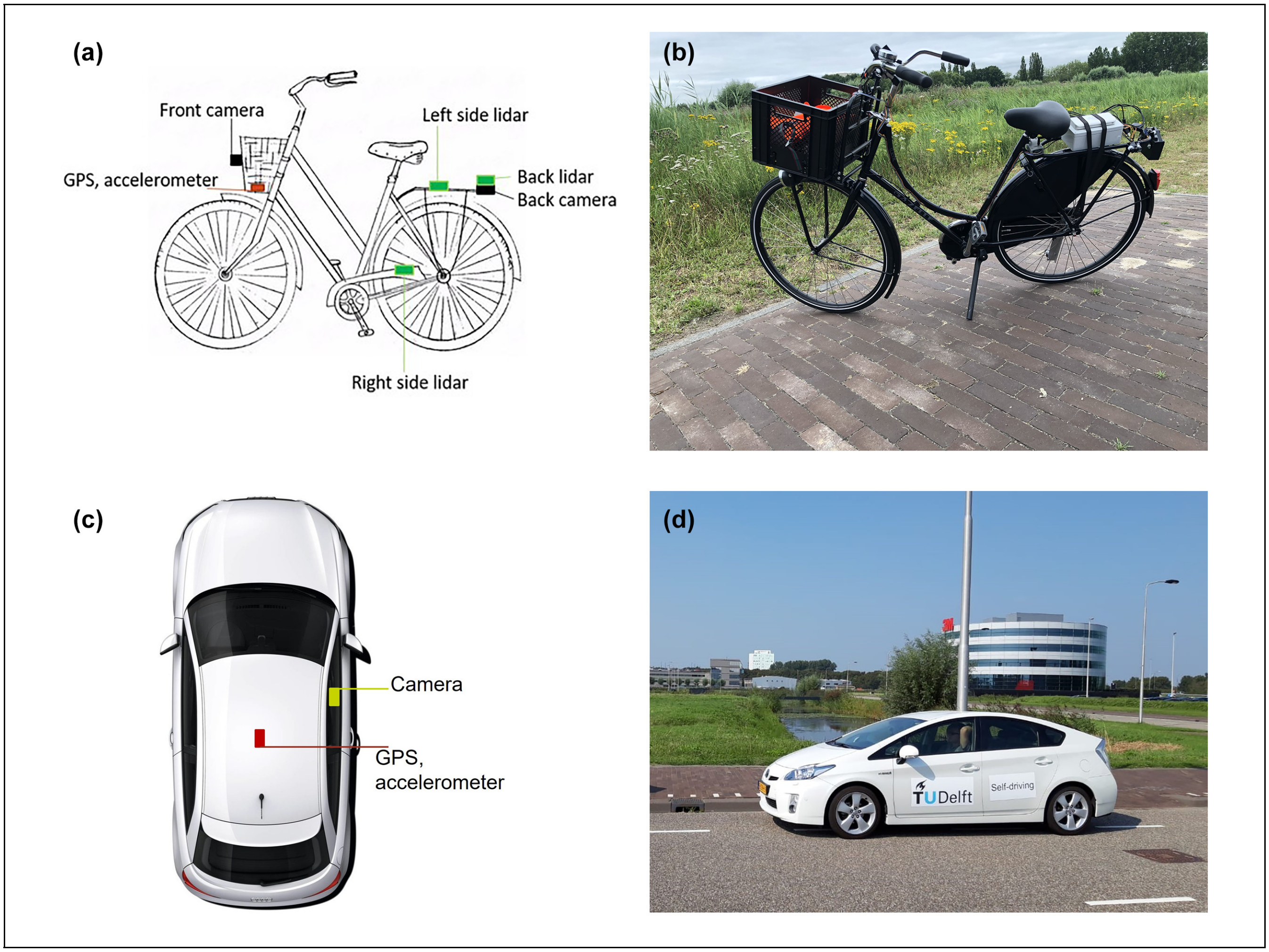

Figure 3. Placement of sensors on the bicycle (*a*) and the instrumented bicycle (*b*); placement of sensors on the vehicle (*c*) and the instrumented vehicle (*d*).

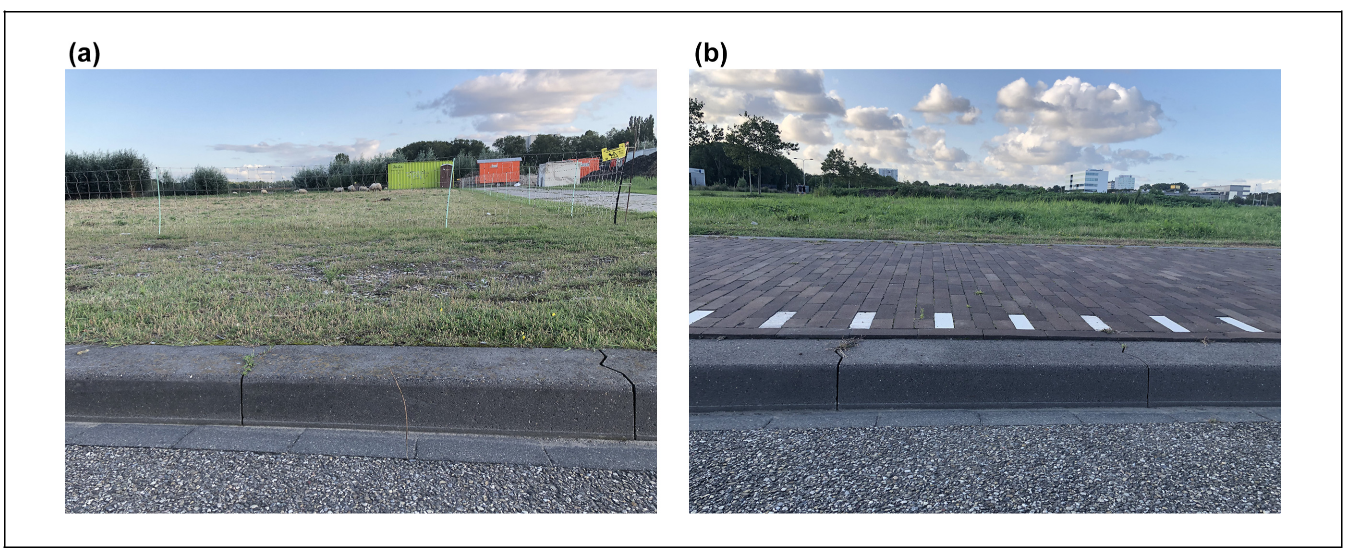

Figure 4. Roadside type: (*a*) grass and (*b*) brick-paved path.

Table 1. Number of Rides per Scenario and Attribute

	Self-reported trust	Subjective risk (%)	Objective risk level (Joules)	Distance to curb (m)	Speed (m/s)
Overall number of rides	194	194	80	176	80
Automated following	49	49	20	44	20
Automated overtaking	51	51	20	45	20
Speed +5 (m/s), lateral distance 1.5 m	14	14	7	13	7
Speed +5 (m/s), lateral distance 3.5 m	11	11	7	10	7
Speed +10 (m/s), lateral distance 1.5 m	12	12	3	11	3
Speed +10 (m/s), lateral distance 3.5 m	12	12	3	11	3
Manual following	47	47	20	44	20
Manual overtaking	47	47	20	43	20
Speed +5 (m/s), lateral distance 1.5 m	11	11	3	10	3
Speed +5 (m/s), lateral distance 3.5 m	12	12	3	11	3
Speed +10 (m/s), lateral distance 1.5 m	11	11	7	10	7
Speed +10 (m/s), lateral distance 3.5 m	13	13	7	12	7

Experiment Procedure. The experiment procedure included an initial pilot experiment followed by the main experiment. The pilot experiment included four cyclists and was used to verify the experiment procedure. Before the field experiment, the participants were asked to complete the personal characteristics questionnaire and their basic level of trust in AV technologies. During the experiment, each participant completed 10 rides of 200 m each. First, the participant completed two rides without any interaction with the vehicle for familiarization with the bicycle. After that, the participant completed an additional eight rides in which they interacted with the vehicle. After each ride, the participants were asked to complete the trust questionnaire, report the level of risk they had experienced during the ride and the attributes influencing their evaluation, and answer whether the vehicle was operated manually or automatically.

Data Collection

Table 1 summarizes the data collected during the experiment. The numbers in the table represent the number of rides for each scenario and attribute. The theoretical total number of rides would have been 250 (25 participants, each did eight scenario rides and two familiarization rides). However, different reasons led to data loss; thus, the total number of rides is less than 250 rides.

Trust and subjective risk levels were reported at the end of each ride. The lateral and longitudinal position of the vehicle relative to the cyclist and the speed of the vehicle and cyclist were recorded at a resolution of five measurements per second. These data were used as an input to calculate the objective risk. Additionally, the LIDAR installed on the bicycle captured the distance of the cyclist to the curb. The mean objective risk was then calculated for each ride and as well separately for the beginning, middle, and end of each ride, as illustrated in Figure 5.

For the following maneuver, the beginning, middle, and ending parts of the route were selected to equal their ride duration.

Analysis Method

The analysis included the objective risk assessment, the subjective risk assessment and self-reported trust, and the subjective and objective risk modeling.

The objective risk was assessed using the probabilistic driving risk field (PDRF) safety approach (*21*), and was calculated every 0.2 s. The PDRF has severity and probability components. The severity component can capture differences in risks between a collision with a highly rigid object and an object of low rigidity. The probability component captures differences in probabilities of collisions between two objects, for example, the difference between two objects moving in parallel versus two objects moving in perpendicular. The PDRF has a benefit over other surrogate safety measures in that it can consider

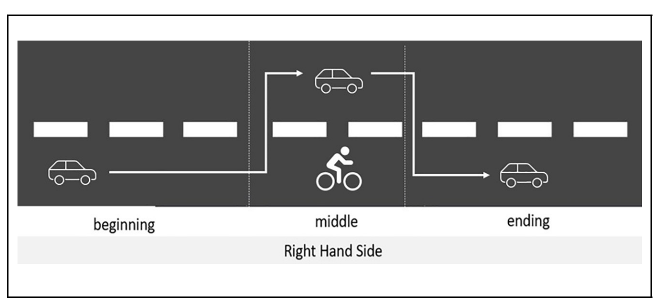

Figure 5. Definition of beginning, middle, and ending of an overtaking maneuver.

simultaneously the risks of collision with static (e.g., guardrail) and kinetic (e.g., moving vehicles) objects.

The potential risk field is associated with threats from static road objects while the kinetic risk field is associated with threats from moving road objects. The total risk is equal to the risks posed by multiple road objects based on the superposition property of fields (*21*).

The potential risk field can be calculated using Equation 1:

$$R_{b,s} = 0.5kM(V_{s,b})^2 \cdot max(e^{\frac{-|r_{s,b}|}{D}}, 0.001) \quad (1)$$

The crash severity is represented by the term $0.5kM(V_{s,b})^2$. The severity is the magnitude of the crash energy that appears in an accident between objects S and B. The unit of measurement of the crash severity is Joules. The term $e^{\frac{-|r_{s,b}|}{D}}$ defines the crash probability, which ranges between 0 and 1.

In Equation 1,

s = a dynamic object experiencing influence from a static object b;

b = a static object influencing a dynamic object s;

k = the parameter of the rigidity of the road boundary object with a range from 0 to 1. In this study, we used $k = 0.61$ for the side of the road with a curb with a brick-paved surface and $k = 0.55$ for a road with a curb and grass side (*22*);

M = the mass of the dynamic object s;

$V_{s,b}$ = the velocity of the dynamic object s along $r_{s,b}$;

$r_{s,b}$ = the vector of the shortest distance between dynamic object s and static object b;

D = the steepness of descent of the potential risk field. In this study $D = \frac{W}{14}$, where W is the width of the object s. The collision probability reaches a value of 0.001 in the center of the lane.

The kinetic risk field can be calculated using Equation 2. The unit of measurement of the kinetic risk field is Joules.

$$R_{n,s} = 0.5M_s\beta^2|\Delta V_{s,n}{}^2| \cdot p(n,s) \quad (2)$$

where

s = a dynamic object that is experiencing risk from another dynamic object;

n = a dynamic object that influences the considering object S;

M_s = mass of the dynamic object S;

M_n = mass of the dynamic object N.

$\beta = \frac{M_n}{M_s + M_n}$ represents the mass ratio of the interacting objects. $\Delta V_{s,n} = V_s - V_n$ denotes the counteracting velocity between dynamic objects s and n. $p(n,s)$ is the probability of a collision (spatial overlap) that ranges from 0 to 1.

The collision probability likelihood is related to the probability distribution of road users' acceleration. We know the trajectory of s and can predict the course of n. As the trajectory of n is unknown, the acceleration is treated as a random variable. The variability of acceleration is represented as normal distribution and is equal to the relative likelihood of occurrence.

The subjective (i.e., perceived) risk was captured by a risk scale of 100 degrees, with higher scores representing a higher risk level.

Failures appear if users misuse automation by over-trusting the system or if users disuse the automation system by under-trusting it (*22*). Trust is not directly observable—people can still cooperate with an automated system even without trusting it (*20*, *23*). Data from sensors that collect skin response and heart rate cannot give valuable insights on trust, as the level of risk in the field experiment is similar to daily stress (*5*). Therefore, the trust was assessed using the questionnaire on trust in technologies (*20*). We asked the cyclists to fill in the questionnaires on the trust level directly after each ride.

The subjective and objective risk modeling were conducted using generalized linear mixed models (GLMM). As each participant completed several scenarios, the observations from the different scenarios of each participant are correlated (*24*). Therefore, GLMMs (with the unstructured covariance matrix) (*25*) were applied with fixed and random effects to account for the correlations among the different observations at the participant level. The developed models were estimated using the Mixed Effect Model command in SPSS 22 (*26*). The fixed effects stand for variables that include all possible study design levels (*24*, *27*). Random effects are variables whose values in the data file can be considered a random sample from a larger population of values. These are variables that have an effect that varies by subject and by item. By-subject variation is originated from the participants' basic features of character and by-item variation accounts for differences in the conditions of each level of each independent variable. To account for variations per participant, a random intercept was assumed. The general form of the GLMM can be written as follows:

$$y = X\beta + Z\mu + \varepsilon \quad (3)$$

where y is a $N \times 1$ column vector, the outcome variable; X is a $N \times$ p matrix of the p predictor variables; β is a p $\times$ 1 column vector of the fixed-effects regression coefficients (the β s); Z is the $N \times$ q design matrix for the q random effects; μ is a q $\times$ 1 vector of the random effects; and ε is a $N \times 1$ column vector of the residuals.

Results

First, we present descriptive statistics of the objective and subjective risk assessment, followed by the GLMM

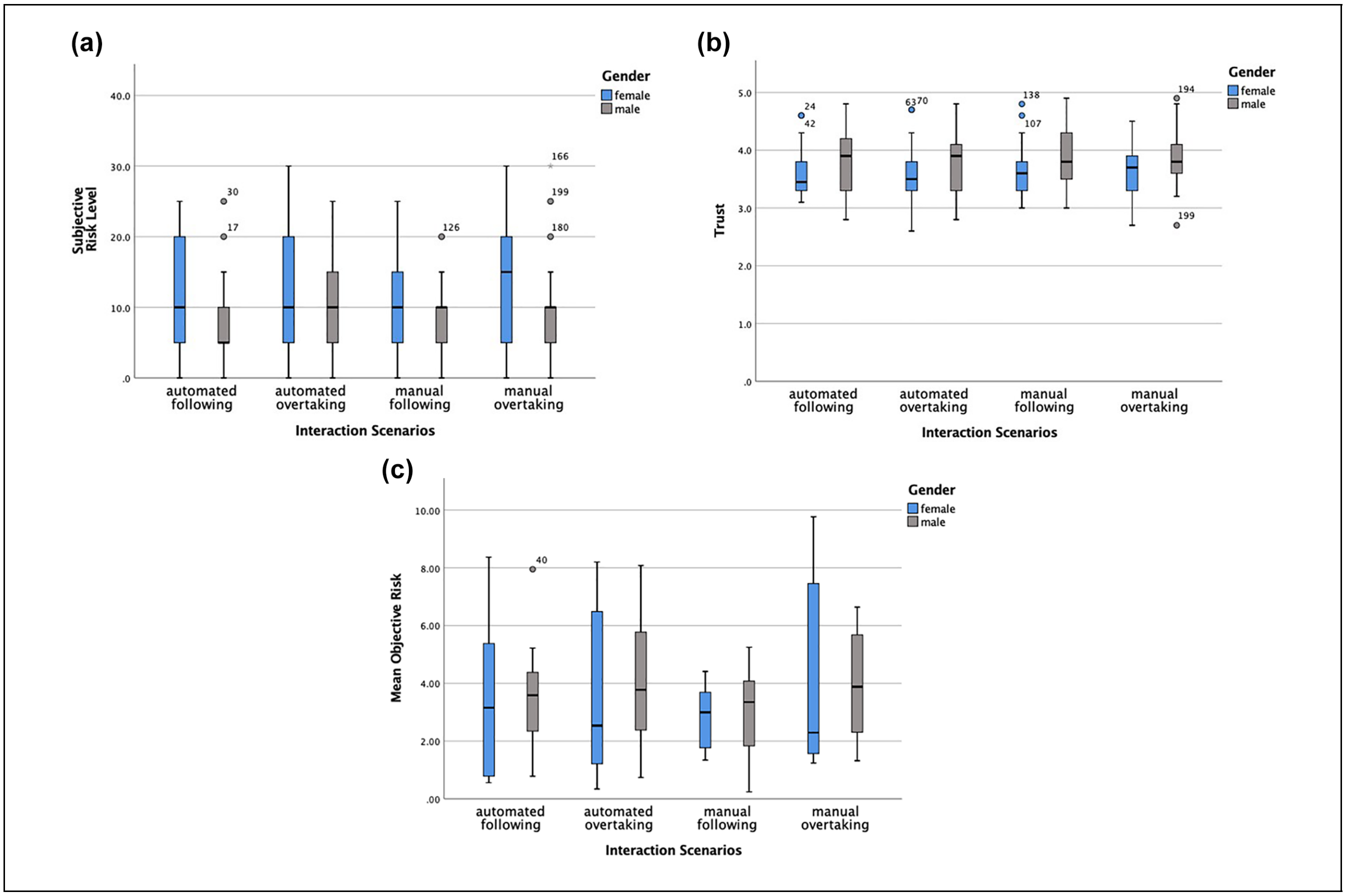

Figure 6. (*a*) Objective risk, (*b*) subjective risk and (*c*) trust level for the different interaction scenarios by gender.

results and a graphical analysis of the cyclists' behavioral change.

Descriptive Statistics of the Objective and Subjective Risk by Cyclists' Personal Characteristics

Figure 6*a* shows that male cyclists have lower subjective risk levels compared with female cyclists and with lower variability. Figure 6*b* shows that male cyclists have higher trust levels in automation than female cyclists. These results might explain the higher levels of objective risk for male cyclists (Figure 6*c*). As male cyclists perceive the interactions to be less risky and have higher trust in the vehicle, they tend to be less cautious and ride closer to the car and with higher speeds.

Descriptive Statistics and Graphical Analysis of the Objective and Subjective Risks

The objective risk during the manual overtaking maneuver was higher than during the manual following maneuver (Friedman test $\chi^2 = 10.80$, $p < 0.001$). Similarly, the subjective risk during the automated overtaking maneuver was higher than during the automated following maneuver (Friedman test $\chi^2 = 5.333$, $p < 0.021$).

However, while evaluating the risk of interaction, it is important to look at the experienced risk and the duration of time when this risk was applicable. With a longer duration of risky situations, the probability of an accident increases. Figure 7 presents a graph of the objective risk changes along the route. In the case of the following maneuver, the risk stays at the same level along the whole route, while in case of an overtaking maneuver, there are two short peaks at the phase of approaching to overtake and returning to the lane.

There is statistical evidence that the subjective risk of the cyclist when the vehicle overtakes with a lateral distance of 3.5 m is lower than the subjective risk when overtaking with a lateral distance of 1.5 m in both automated and manual driving modes (Friedman test $\chi^2 = 5.762, p < 0.016$; T-test $t(62) = 3.054, p < 0.003$, respectively). However, there was no statistical evidence that cyclists changed their mean distance to the curb when they interact with vehicles in different driving modes.

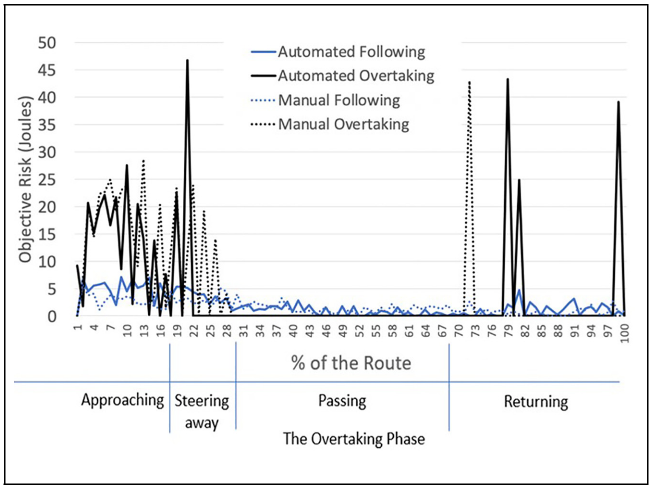

Figure 7. Objective risk along the route.

Modeling the Objective and Subjective Risks

To understand the variables that can explain the subjective and objective risks, the GLMM was applied. Table 2 presents the results.

According to the GLMM model for the subjective risk dependency on the independent variables (Table 3), the trust improvement in one unit reduces predicted subjective risk in −6.690. Furthermore, the model shows a statistically significant ($p = 0.042$ and $p = 0.039$) relationship between interaction scenarios and subjective risk. The magnitude of the automated following is equal to 5.521, while the magnitude of the automated overtaking is 5.930. A pairwise comparison shows a statistically significant ($p = 0.033$) relationship between automated overtaking and manual following with a magnitude of 2.744.

Table 2. Fixed Effects of the Generalized Linear Mixed Model for the Subjective and Objective Risks

	Subjective risk			Objective risk		
	Coefficient	Standard error	t-Value	Coefficient	Standard error	t-Value
Intercept	39.942	8.677	4.603**	10.085	1.721	5.861**
Trust	−6.690	1.379	−4.852**	na	na	—
Automated following	5.521	2.671	2.067*	−4.550	0.516	−8.816**
Automated overtaking	5.930	2.825	2.099*	0.636	0.300	2.119*
Manual following	3.186	2.790	1.142	−4.870	0.526	−9.252**
Manual overtaking	4.265	2.844	1.499	0	na	na
No interaction with the vehicle	0		na	na	na	na
Relative distance	na	na	na	−0.426	0.033	−13.026**
Max. cyclist speed	−0.213	0.912	−0.234	−0.486	0.199	−2.435*
ROADSIDE = curb with a brick-paved surface	−0.539	0.825	−0.654	−1	0.194	−5.146**
ROADSIDE = curb with grass	0	na	na	0	na	na

Note: Max. = maximum.
*$p < 0.05$; **$p < 0.01$; na - not applicable.

Table 3. Fixed Effects of the Generalized Linear Mixed Model for Trust

	Trust		
	Coefficient	Standard error	t-Value
Intercept	3.520	0.459	7.662**
Automated following	0.628	0.118	5.307**
Automated overtaking	0.478	0.139	3.436**
Manual following	0.629	0.123	5.098**
Manual overtaking	0.536	0.141	3.797**
No interaction with the vehicle	0	na	na
Subjective risk level	−0.024	0.005	−4.672**
Max. objective risk	0.004	0.002	2.125*
Mean distance to the curb	−0.792	0.366	−2.225*
Max. cyclist speed	0.131	0.054	2.414*

Note: Max. = maximum.
*$p < 0.05$; **$p < 0.01$; na - not applicable.

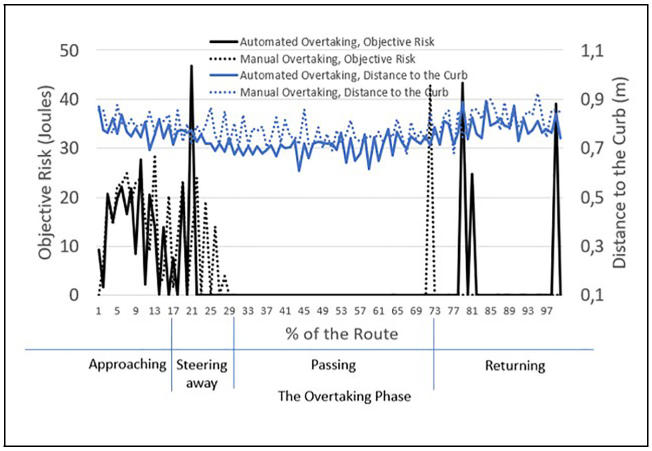

Figure 8. Objective risk and distance to the curb along the route (mean distance at approaching and steering = 0.77 m; passing: 0.76 m; returning: 0.78 m; maximum distance at approaching and steering = 1.04 m; passing: 0.96 m; returning: 1.12 m).

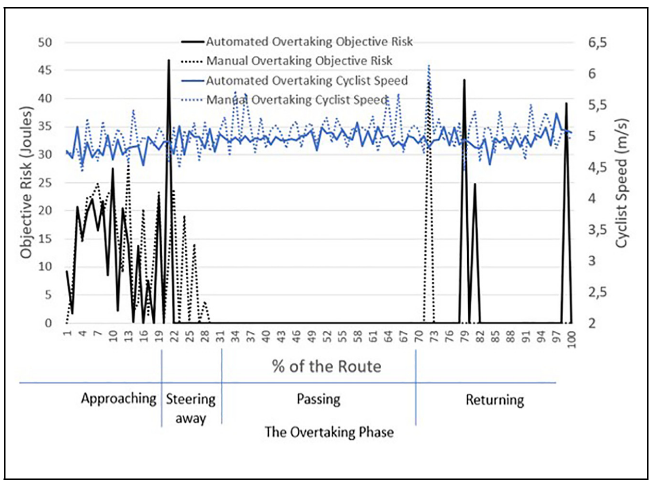

Figure 9. Objective risk and cyclists' speeds along the route (mean speed at approaching and steering = 4.96 m/s; passing: 4.99 m/s; returning: 5.0 m/s).

The GLMM model for the objective risk dependency on the independent variables (Table 3) showed that there is a statistically significant ($p < 0.0001$) relationship between right-hand side object and objective risk. The curb side with a brick-paved surface has one Joule objective risk less than the curb with the grass side. Objective risk and the cyclist speed has a statistically significant ($p = 0.015$) relationship. With the increase of cyclist speed of 1 m/s, the objective risk declines by 0.486 Joules. The relationship between relative distance and objective risk is also statistically significant ($p < 0.0001$). With an increase of the distance between the vehicle and cyclists of 1 m, the objective risk reduces by 0.426 Joules. A statistically significant relationship exists between the interaction scenarios and objective risk level. Overall, the lowest objective risk in comparison with the manual overtaking is found in manual following. In contrast, automated following has a slightly higher risk level, and the highest risk level out of all interaction scenarios has automated overtaking.

Modeling of the Trust Level

For the GLMM model of the dependency of trust level on the independent variables (Table 3), the random effect of the subjective risk level was significant. However, the best model fit was the model with the random intercept (Akaike corrected criterion = 115.354; Bayesian = 139.3). In comparison with the no vehicle interaction scenario, the highest level of trust was found with automated following ($p < 0.0001$, magnitude = 0.628) and manual following ($p < 0.0001$, magnitude = 0.629). Manual overtaking has a lower trust ($p < 0.0001$, magnitude = 0.536) and automated overtaking has the lowest trust ($p = 0.001$, magnitude = 0.478). There is a statistically significant ($p < 0.0001$) relationship between subjective risk level and trust level. With an increase of the trust of one unit, the subjective risk level decreases by 0.024. There is a statistically significant ($p = 0.036$) relationship between maximum objective risk and trust level. With an increase of trust level of one unit, the maximum objective risk increases by 0.004. The mean distance to the curb decreases with the increase of trust level ($p = 0.029$). Two participants with a difference of one unit of trust will have a difference in mean distance to the curb of 0.792 m. Maximum cyclist speed increases by 0.131 with a one unit increase in trust level ($p = 0.018$).

Descriptive Statistics and Graphical Analysis of the Cyclists' Behavior

Figures 8 and 9 show that in the overtaking scenario, during the passing stage, cyclists start cycling closer to the curb, slightly increasing speed, then revert to the original distance and speed after the vehicle returns to the lane in front of the cyclist. The distance to the curb has slightly lower values for the automated driving mode than for the manual driving mode. The speed has higher values for the manual overtaking scenarios compared with the automated overtaking scenarios, as the trust level for manual driving is higher than for automated driving. Thus the basic speed was consistently higher for manual driving than for automated driving.

In the after-experiment interview, the participants reported the attributes that influenced their subjective risk level. For automated overtaking, manual overtaking, and manual following scenarios the most influencing

Table 4. Share of Attributes That Affect the Subjective Risk Level for all Maneuvers and Modes

Attribute	Share (%)
Distance to the vehicle	31
Vehicle characteristics (size/noise)	24
Speed of the vehicle	20
Vehicle driving mode (automated/manual)	15
Attentiveness of the driver	5
Objects on the right-hand side (curb)	5

attributes are the distance to the vehicle, the vehicle characteristics (size/noise), and the speed of the vehicle. For the automated following scenario, additional importance was given to the vehicle having an automated driving mode. Table 4 shows the attributes reported as influencing factors across all interaction scenarios (all modes and maneuvers) in descending order.

Discussion and Conclusion

The research investigates which AV behavior, following or overtaking, results in the lowest subjective and objective risks of interaction when approaching a cyclist from behind. Additionally, the study provides information on the changes in cyclists' behavior when interacting with AVs compared with interacting with conventional vehicles. This section discusses the results and compares them with the results obtained in other relevant studies, and finally concludes the paper.

In this research, we found that the participating cyclists felt less safe, increased their cycling speed, and reduced the distance to the curb when being overtaken by an AV. However, there was no difference in the cycling behavior and risk perception between automated and manual scenarios when the vehicle followed the cyclist. These findings are in line with previous studies of road users' interactions with AVs (*2–5*, *10*) which showed that pedestrians generally feel less safe and behave more cautiously when interacting with AVs.

The analysis shows that female participants experience lower trust and higher subjective risk and tend to cycle closer to the curb during overtaking maneuvers. Yannis et al. (*9*) reported that the gender of participants influences their trust in interaction with AVs.

Cyclist's speed was found to increase during overtaking scenarios. In a follow-up interview with the cyclists at the end of the experiment, the cyclists mentioned that they prefer a shorter passing time of the vehicle. Chuang et al. (*19*) confirmed this result, as they found that longer passing time led to an observed increase in cyclist's speed.

The danger of over-trust in automated systems was mentioned by Lee and See (*28*). The current study included participants with different levels of trust. Participants with higher trust levels cycled at a much higher speed than cyclists with lower trust. However, the correlation between trust level and cycling experience is still not fully understood.

From the post-experiment interview it was found that the factors having most influence on the cyclists' trust levels are the vehicle's speed and distance. The same results were highlighted by several scientific studies (*8–10*, *12*, *17*, *18*, *29*). The second most influencing factor was the vehicle characteristics, which stand for the size of the vehicle and the noise it makes. This finding is in line with results from Llorca et al. (*12*)

There is clear evidence that the overtaking scenario resulted in higher subjective and objective risk levels than the following scenario. However, the time of the interaction also has a significant impact on the cyclist's behavior. Toward the end of the following scenarios cyclists increased their cycling speed. They started looking over their shoulder to see the following vehicle, leading to loss of balance and a closer distance to the curb. In the overtaking scenarios, during the passing stage, the cyclists reduced their distance to the curb and increased their cycling speed, which resulted in a higher objective risk. The interaction time was lower in the overtaking scenarios than in the following scenarios. Thus, we can conclude that, for short distances, the following scenario is a safer option. Besides the exact vehicle maneuver, operation modes also influence the risk levels. For the following scenario, there is no apparent difference between the automated and manual modes. For the overtaking scenarios, the automated mode has higher subjective and objective risk levels than the manual driving mode.

The available relative lateral distance influences the risk of the interaction scenario. The greater the lateral distance, the lower the risk. For the street broader than 3 m, the overtaking scenarios had the same subjective risk as the following scenarios. In comparison, for the road narrower than 1.5 m, the overtaking scenarios had higher subjective risk than the following scenarios. Besides overtaking with a greater relative lateral distance, another point of attention could be the overtaking speed (this study assessed speeds below 40 km/h). With a higher but still safe speed, the interaction time is reduced.

The study results provide insights for vehicle manufacturers to improve the behavior of AVs. Driver licensing authorities can use this study's insights to increase drivers' awareness about the nature of potential risks when interacting with cyclists.

Despite the promising results, this study has some limitations. In future research, we advise using a naturalistic experiment with an AV to eliminate changes in participants' behavior arising from the design of the investigation. A naturalistic experiment will also help collect more realistic estimations of the subjective risk, as participants will evaluate subjective risk more realistically outside the clear experiment setups. Another limitation stems from the discrete nature of the subjective risk. Values were collected one time per ride, and we do not know exactly which point of time in a ride reflects the reported amount of risk. In the current study, the vehicle was always manually driven (we instructed the drivers how much distance to keep from the cyclist). Therefore, a limitation of this study is that the results reflect how cyclists respond to AVs which are programmed to drive in the same way as human drivers. If the driving style of future AVs were to be different from average human driving style, the reaction of cyclists and their subjective risk could differ from those observed in this research.

It is also recommended that future research should recruit participants with different ages and experience levels. Participants with a lower experience levels could have different behavior. We included only experienced cyclists in the current research to maintain a good safety level. With bigger samples of participants, it would also be possible to investigate the reactions of cyclists from different age groups.

Another interesting consideration for future research could be not to inform cyclists in advance about the vehicle's driving mode (automated/manual) but to ask cyclists at the end of the ride what the vehicle's driving mode was.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: M. Oskina, H. Farah, P. Morsink, R. Happee, B. van Arem; data collection: M. Oskina; analysis and interpretation of results: M. Oskina, H. Farah, P. Morsink, R. Happee, B. van Arem; draft manuscript preparation: M. Oskina, H. Farah, R.Happee. All authors reviewed the results and approved the final version of the manuscript.

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Data Accessibility Statement

The row data collected during the field experiment is partly publicly accessible.

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