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# Understanding the interaction between cyclists and motorized vehicles at unsignalized intersections: Results from a cycling simulator study

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## ABSTRACT

**Introduction:** With cycling gaining more popularity in urban areas, it is vital to obtain accurate knowledge of cyclists' behavior to develop behavioral models that can predict the cyclist's intent. Most conflicts between cyclists and vehicles happen at crossings where the road users share the path, especially at unsignalized intersections. However, few studies have investigated and modeled the interaction between cyclists and vehicles at unsignalized intersections. **Method:** A bike simulator experiment was conducted to scrutinize cyclists' response process as they interacted with a passenger car at an unsignalized intersection. An existing unsignalized intersection in Gothenburg was simulated for test participants. Two independent variables were varied across trials: the difference in time to arrival at the intersection (DTA) and intersection visibility (IV). Subjective and quantitative data were analyzed to model the cyclists' behavior. **Results:** When approaching the intersection, cyclists showed a clear sequence of actions (pedaling, braking, and head turning). The distance from the intersection at which cyclists started braking was significantly affected by the two independent variables. It was also found that DTA, looking duration, and pedaling behavior significantly affected cyclists' decisions to yield. Finally, the questionnaire outputs show that participants missed eye contact or communication with the motorized vehicle. **Conclusions:** The kinematic interaction between cyclists and vehicles, along with the cyclist's response process (visual and kinematic), can be utilized to predict cyclists' yielding decision at intersections. From the infrastructural perspective, enhancing visibility at intersections has the potential to reduce the severity of interactions between cyclists and vehicles. The analysis of the questionnaire emphasizes the significance of visual communication between cyclists and drivers to support the cyclist's decision-making process when yielding. **Practical applications:** The models can be used in threat assessment algorithms so that active safety systems and automated vehicles can react safely to the presence of cyclists in conflict scenarios.

## 1. Introduction

Cycling as an active mode of transport is increasing across European countries (Pucher & Buehler, 2017). With increasing cycling mobility in urban areas, it is getting more critical to assure cyclists' safety (Cantisani et al., 2019). European crash data show that cyclists' share of fatalities is increasing, while the trend for operators of motorized vehicles is the opposite. Crossings are the most common place for conflicts between bicycles and motorized vehicles, and these encounters are more critical at unsignalized intersections (Bjorklund, 2005). In fact, Isaksson-Hellman and Werneke have shown that over 70% of bicycle crashes occur in areas where cyclists share the path with motorized vehicles (Isaksson-Hellman & Werneke, 2017). Active safety systems and

automated vehicles (AVs) are expected to improve the cyclists' safety by predicting the cyclists' intent and acting to maximize interaction safety (Reyes-muñoz & Guerrero-ibáñez, 2022). Although recent studies have shown that with a 100% penetration rate of AVs, conflicts between bicycles and AVs will decrease, AVs still need to be trained to behave safely when encountering bicycles (Tafidis et al., 2019). For a successful implementation of AVs in urban areas, AVs need to understand the intent of vulnerable road users. The three main phases that enable AVs to operate are continual detection, prediction, and path planning (Visser et al., 2017). A similar concept also applies to active safety systems, which operate based on threat assessment algorithms to detect dangerous scenarios. According to Ljung Aust and his colleagues (Aust et al., 2023), active safety systems have three main phases: detection,

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decision strategy, and intervention strategy. The detection phase mainly makes use of the vehicle's sensors to collect data, and the decision phase uses the processed data to determine whether an intervention needs to be issued. Interventions can be in the form of a warning or an autonomous intervention. These phases are important for the successful implementation of AVs and active safety systems to avoid intervening too early or too late. Both active safety systems and automated vehicles require a good understanding of the bicycle-vehicle interaction process to determine if an intervention is required, and computational models are an obvious way for machines to understand human behavior.

A few studies have tried to investigate and model the interaction between automated vehicles and bicycles at crossing scenarios (Hagenzieker et al., 2020). However, the effects of some variables on cyclists' interactions with vehicles (notably, obstructed field of view at intersections and time to arrival) have not been sufficiently investigated in the literature. A few studies have been performed recently to investigate and model the interaction between bicycles and vehicles at an unsignalized intersection. Silvano et al. (2016) collected data through field observation by recording videos at an unsignalized roundabout and developed a two-stage logistic model to predict cyclists' yielding behavior using kinematic information (speed and distance). They found that time to arrival at the intersection and the vehicle's speed significantly affect the cyclist's decision whether to yield. However, their work took place at a roundabout rather than an unsignalized intersection, and the authors did not use a complete trajectory dataset. The data that were used in their study only included the presence of bicycle and the car at discrete locations at the intersection. Bella and Silvestri (2018) used a driving simulator to analyze the effect of different infrastructure designs on driver's response process. They investigated the efficacy of different safety countermeasures (like pavement color and raised islands) at reducing drivers' speed when they interacted with a cyclist at the crossing. Using data from 36 participants and employing descriptive statistics, they aimed to answer the question of which infrastructural modifications contribute to safer cyclist-vehicle interactions. Additionally, they reported questionnaire responses from the tests, where participants mentioned that colored paved markings had an impact on reducing their speed. Velasco et al. (2021) showed videos of oncoming vehicles approaching from the left side of the intersection to participants in a virtual reality (VR) headset. In the video, the participants were cycling toward an unsignalized intersection, and they needed to decide whether to cross or yield. Their yielding decision model was tested with parameters such as gap distance, stated trust in vehicles, types of vehicles, and priority to cyclists. They used multinomial logistic mixed regression to observe the factors that were statistically significant in cyclists' crossing decisions. They found that the distance to the car and whether the cyclist has the right of way were the primary factors affecting the cyclist's decision to cross the intersection.

Simulators have gained popularity for investigating cyclists' behavior for several reasons. They provide a controlled environment that makes it possible to obtain a homogenous dataset. Another advantage is that in a conflict scenario (like in this study), participants will not be subjected to any harm, and the scenarios can be repeated. In addition, one can set up an experiment faster and at a lower cost than on a test track. As noted, simulators have recently been used to observe the interaction between bicycles and vehicles. However, driving simulators are mostly used to investigate the process of overtaking cyclists (Calvi et al., 2022; Dols et al., 2021; Farah et al., 2019); only one study was found that used a driving simulator to investigate the bicycle-vehicle interactions at an unsignalized intersection (Boda et al., 2018). They considered three independent variables, which consisted of bicycle speed, vehicle speed, and configuration for arrival to model the gas pedal release time and brake onset time of drivers using linear mixed-effect models. It is noteworthy that they identified the cyclist's visibility as the primary factor influencing the driver's response process during the interaction with cyclists.

In recent studies, cyclists' visual information, along with kinematics,

has been proven important in predicting cyclists' behavior. Implicit and explicit communication methods are essential for signaling intent among road users. They can also be useful for prediction models (Lundgren et al., 2017). Most prediction models have been developed to deal with pedestrian-vehicle interactions, and very few studies have tried to quantify the role of visual information in predicting cyclists' behavior (Mahadevan et al., 2018). Hemeren et al. (2014) showed videos of cyclists crossing an intersection to a group of participants and asked them which visual cues were more relevant for predicting the cyclist's future path. In the videos, the cyclists were either going straight or turning left at the intersection. The authors found that the cyclist's speed, head turn, and position (leaning or sitting up straight) were the most important cues for predicting the cyclist's intention to go straight or turn left. Other studies have also tried to find connections between visual cues and cyclists' intentions; Abadi et al. built a neural network model to predict cyclists' crossing intention using cyclists' head orientation (Abadi & Goncharenko, 2022). A deep understanding of cyclists' response process in terms of their actions will help to devise more accurate behavioral models for the application in AVs and active safety systems.

The present study aims to give insight into the interactions between bicycles and motorized vehicles at unsignalized intersections. In this study, the following research objectives were defined: (a) to observe the cyclists' response process when they approach the intersection under different configurations of time to arrival and visibility of the approaching vehicle; (b) to assess the effect of different variables on cyclists' braking onset and yielding decision; and (c) to examine the usefulness of the cycling simulators for evaluating bicycle-vehicle interactions. A fixed-base bicycle simulator was used in this study to achieve the objectives.

This paper is organized as follows. The material and methods section outlines the design and execution of our study, including details on participants, experimental design, tools, and data analysis. The results are then presented in the subsequent section, offering insights into how the independent variables affected the cyclists' responses during the interaction with the approaching vehicle. Finally, the discussion and conclusion summarize the key findings, discuss their implications, and point to potential avenues for future research.

## 2. Materials and methods

### 2.1. Participants

The inclusion criteria for this experiment required participants to ride a bike at least once a week, be between 18 and 45 years old, not have a physical disability, not wear prescribed eyeglasses, and have a height under 185 cm. We specifically targeted people with cycling experience, establishing a criterion of cycling at least once a week to ensure that the participants were frequent cyclists. Additionally, we set the age limit at 45 years old, considering our observation in the pilot tests that older individuals are more prone to experiencing motion sickness in the simulator. The final criteria were the absence of prescribed eyeglasses due to the head-mounted display and the height under 185 cm due to the physical constraints of the bike simulator, which could not accommodate taller people. The participants were recruited through online advertisements in social media and by contacting people from previous experiments. Twenty-seven people participated in the study and rode the bicycle simulator. This research complied with the tenets of the Declaration of Helsinki and was approved by the national ethical review board (Dnr: 2021-01933). All participants signed a consent form prior to participation in the experiment.

### 2.2. Riding simulator and experimental setup

The bicycle simulator (Fig. 1) was developed by VTI (the Swedish

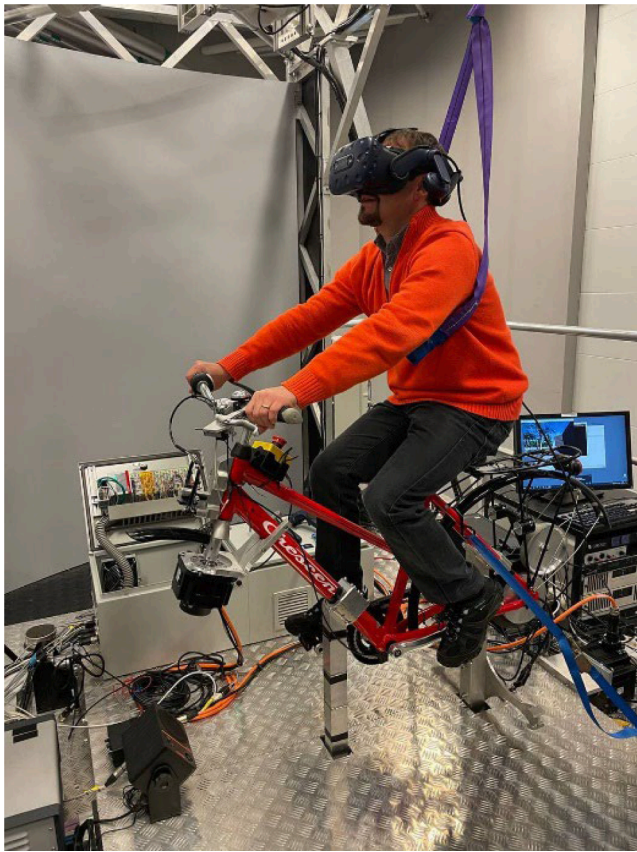


Fig. 1. Bike simulator with virtual-reality headset.

Road and Transport Research Institute) and the experiment was carried out in Gothenburg, Sweden. The 3D environment was built using Unreal Engine, and the exclusive simulation software was developed by VTI. The participants rode the custom-made instrumented bicycle wearing a virtual-reality headset that showed the simulated environment. The virtual headset was a VIVEPRO, with a  $1440 \times 1600$  pixels-per-eye resolution and a field of view of 110 degrees.

In the experiment, all participants were asked to ride the instrumented bicycle in the simulator in a dedicated bike lane (Fig. 2a) and to

cross the unsignalized three-way intersection (shown in Fig. 2a–b) several times. Participants were explicitly told before the experiment that they would interact multiple times with a driverless vehicle coming from the right. The vehicle had tinted windows and, therefore, the participants could not see inside the vehicle. The intersection recreated, as closely as possible, a real intersection in Gothenburg, Sweden (GPS coordinates:  $57^{\circ}42'31.1''N$ ,  $11^{\circ}56'22.9''E$ ). According to Swedish traffic rules, bicycles have the right of way over motorized vehicles at intersections, so they may cross first; but cyclists should also pay attention to surrounding vehicles and cross the intersection carefully. The participants, instructed to cycle and behave as they normally would in real traffic, crossed the intersection 12 times during the experiment. Before the experiment, the participants performed a test run to get acquainted with the bike simulator and get used to turning and braking. In the trials, they started cycling 180 m away from the intersection, and their maximum speed was set to 18 km/h. A virtual trigger was used to activate the passenger car (Volvo XC90, Fig. 2a), which approached the intersection from the right side, when the cyclist was 160 m from the intersection. The vehicle's speed—when it was first visible to the cyclist—was set to 25 km/h and it gradually decreased until the vehicle had passed through the intersection. Both the bicycle's and the vehicle's speeds were chosen based on field observations of the actual intersection by using average speeds. The speed profile of the passenger car followed a polynomial function, whose parameters depended on the forecasted arrival time at the point of intersection of the trajectories of the bicycle and the passenger car and the trial specifications. A truck was parked at the corner of the intersection to limit the cyclist's view (Fig. 2b), and its position was changed across trials to investigate the effect of visibility on the interaction between the bicycle and the car.

We chose the difference in time to arrival at the intersection (DTA) and the intersection visibility (IV) as independent variables for this experiment. The DTA was defined as the time difference between the time instants at which each road user would have reached the intersection point of their trajectories. For the calculation of DTA, we employed a constant speed equal to the one at which each road user traveled at the beginning of the intersection. The DTA was calculated when the participant reached the virtual trigger, activated when the bike arrived at 160 m distance to the intersection. The IV was defined as the distance between the passenger car and the intersection along the vehicle's path (Fig. 2b). The IV was changed by moving the truck that was parked at the corner of the intersection as a method to obstruct the cyclist's view. A full factorial design was applied, in which the DTA had three levels (1.2 s, 2.5 s, and 3.5 s) and the IV had two (22 m and 27 m).



Fig. 2. Layout of the intersection simulated in the experiment; (a) cyclist view of the intersection, (b) top view of the intersection.

**Table 1**

Configuration of trials (\*Indicates trials used for the analysis; NA stays for not applicable).

Trial number	DTA(s)	IV (m)	Trial description
1	2.5	27	Vehicle yields
2*	2.5	22	Vehicle drives through
3	NA	NA	Empty intersection
4	2.5	22	Vehicle yields
5*	1.2	22	Vehicle drives through
6	NA	NA	Empty intersection
7*	2.5	27	Vehicle drives through
8	1.2	22	Vehicle yields
9	NA	NA	Empty intersection
10*	3.5	22	Vehicle drives through
11*	3.5	27	Vehicle drives through
12	2.5	22	Surprise event

Positive DTA values show that the cyclist arrived first at the intersection by the defined values. One trial (IV = 27 m, DTA = 1.2 s) was removed from the full factorial design since the pilot test identified it as an extreme condition, and we were afraid that it might have increased the risk of motion sickness. Three trials with empty intersections were added to the experiment: in these trials, no vehicle approached the intersection. Further, three additional trials in which the vehicle yielded to the cyclist were also added to the experimental protocol. Both the trials with empty intersections and the trials in which the vehicle yielded to the cyclist were intended to reduce the cyclist's expectancy about the oncoming vehicle and were not considered for the analysis. One surprise trial was added at the end, in which the interacting vehicle was a truck instead of a passenger car. The full configuration of 12 trials for each participant can be seen in Table 1. All trials were randomized except for the empty intersections and the last trial (surprise event). There were four groups for the randomization of the trials, and each group consisted of a specific order of trials.

### 2.3. Data analysis

At first, it was investigated whether there was a learning effect due to the experimental setup. Since the trials were randomized between participants, trials happened in different orders for different groups of participants. The time at which participants stopped pedaling was used as a proxy to check if there were any expectations created by the first trial that changed participants' behavior in the following trials. A specific trial was chosen to investigate the learning effect (DTA = 2.5 s, IV = 27 m), which was the 2nd trial for one group and the 7th for the other. The longitudinal distance at which each group started to stop pedaling was extracted from the data to evaluate a possible learning effect. To compare the average longitudinal distances, a 2-tailed *t*-test was used ( $\alpha = 0.05$ ).

#### 2.3.1. Cyclists' action sequence

To investigate the cyclists' behavior as they approached the intersection, three actions were analyzed: pedaling, braking, and head movement toward the oncoming vehicle. Pedaling speed was obtained from the data, and the time stamp at which pedaling speed started to decrease was marked for each participant. Braking point was extracted when the participants reached the maximum brake force. The head yaw rate (obtained from the VR headset) was used to analyze the head movement. If the participants turned their head more than 15 degrees (from the center line of peripheral view) toward the oncoming vehicle, that point was considered to be the time they looked at the vehicle for the first time. We could not find a suitable reference in the literature for choosing a head-turning threshold, so 15 degrees were chosen after reviewing all the head yaw rate signals in the data. This threshold was selected by analyzing and comparing the cyclists' yaw rates before the intersection (in the straight part of the road) and in the intersection area. In a straight path, cyclists rarely turned their head to right and left to

more than 15 degrees, but in the intersection area they turned their head more frequently to more than 15 degrees to monitor vehicle's behavior.

#### 2.3.2. Cyclists' braking onset model

Linear mixed effect models were used to estimate the effects of the independent variables on the distance at which cyclists started braking, calculated on longitudinal axes. These models combine fixed effects, which represent population-level relationships, with random effects, which capture individual variability or group-specific variations. The general form of a logistic mixed-effect model can be expressed as in Equation (1), where  $y$  represents the response variable,  $X$  is the design matrix for fixed effects,  $\beta$  the vector of fixed effects,  $Z$  the random-effects regressor matrix,  $\alpha$  the vector of random effects, and  $\epsilon$  the observation error vector.

$$y = X\beta + Z\alpha + \epsilon \quad (1)$$

#### 2.3.3. Cyclists' yielding decision

Linear mixed-effect models were used to estimate the effects of the independent variables on cyclists' yielding decision. Random effects in mixed-effect models control for the differences between participants in the model. In this paper, a mixed-effect logistic regression was used. The general form of a logistic mixed-effect model can be expressed as in Equation (2), where  $P$  is the probability that a case is in one category,  $X$  the fixed-effect regressor matrix,  $\beta$  the vector of fixed effects,  $Z$  the random-effects regressor matrix,  $\alpha$  the vector of random effects, and  $\epsilon$  the observation error vector.

$$\log\left(\frac{p}{1-p}\right) = X\beta + Z\alpha + \epsilon \quad (2)$$

#### 2.3.4. Modeling speed profiles

Cyclists' speed profiles were modeled as they approached the intersection with respect to time. An arctan function with four coefficients was used to fit each individual cyclist's speed profile. The equation includes three scaling factors ( $a$ ,  $b$ , and  $c$ ) and an offset factor ( $d$ ). Each trial's average speed profile was depicted by the mean speed profile with related 95 % corridor. The fit was performed using the MATLAB fit function, and the least absolute residual method was used to minimize the effect of outliers. The equation that was used to fit the speed profiles is as follows:

$$Y = a \cdot \arctan(bt + c) + d \quad (3)$$

### 2.4. Questionnaires

Two questionnaires were designed to ask participants about their experience during and after the experiment and to obtain information about their demographics. The first was a misery scale (MISC) questionnaire to quantify to what extent participants were affected by motion sickness (Velasco et al., 2021). The scale goes from 0 to 10, with 0 indicating that participants did not have any symptoms, and 10 meaning that participants were throwing up. This questionnaire was filled out during the test (participants were asked to provide a number regarding their level of motion sickness after passing each intersection) and at the end. The second questionnaire was mainly about the demographics and participants' experience in the simulator. Two open questions were posed to capture participants' comments about the scenario and the experiment: (a) How would you compare the scenario to real life? (b) How can we improve the simulator?

## 3. Results

### 3.1. Descriptive statistics

The 27 participants who joined the study had an average age of 32.7 years (STD = 8.0) and the ratio of females to males was 33%. Out of 27

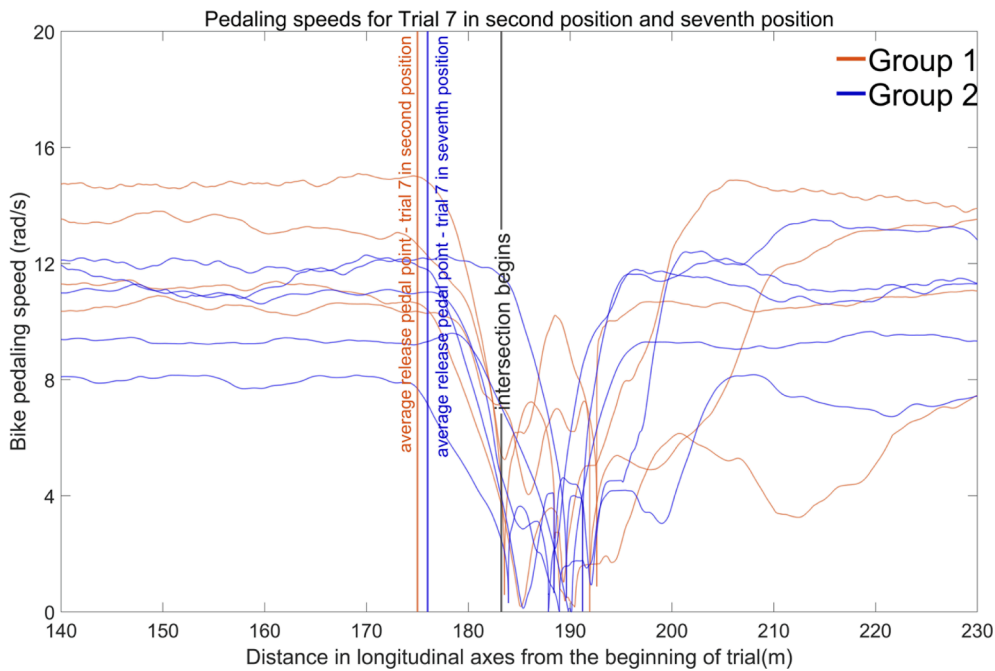


Fig. 3. Average distance from intersection at which participants stopped pedaling for the two groups of participants (who completed Trial 7 in different positions in the sequence).

participants, two experienced motion sickness during the training, so they did not start the actual experiment. The remaining 25 participants (average age = 33 years, STD = 8.5) completed, on average, 8 out of 12 trials because we stopped the experiment as soon as any mild symptoms of motion sickness appeared.

Regarding the learning effect, as shown in Fig. 3, both groups began to stop pedaling at almost the same longitudinal distance from the beginning of the trial. Group 1 and 2 had 5 and 4 participants, respectively. The result from the two-sample *t*-test showed that the difference between means of this location was not statistically significant (with a 5% significance level), and both means are shown as equal. This implies that the likelihood of the data being influenced by the participants' expectations is relatively minimal. Including trials with empty

intersections and trials with the vehicle yielding to the bicycle may have helped decrease participants' expectancy. Furthermore, we included the trial's order as a variable in the computational models to examine this concern, and details will be presented in subsequent sections.

### 3.2. Cyclists' action sequence

The cyclists followed the same sequence of actions as they approached the intersection: first they stopped pedaling, then braked, and then turned their head toward the passenger car. The only exception was Trial 5 (IV = 22 m, DTA = 1.2 s), in which the cyclists looked at the vehicle before they braked (see Fig. 6). Figs. 5–9 present the five trials designated for analysis (see Table 1 for a description of these trials) plus

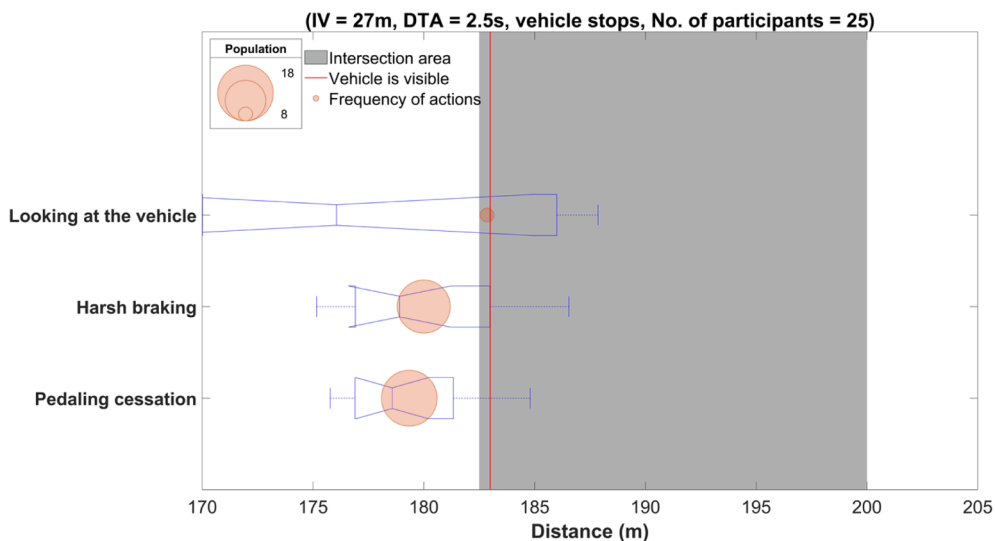


Fig. 4. Sequence of actions in Trial 1 (Boxplots show the median, 95% confidence interval around the median, 25th percentile, and 75th percentile. Grey area in the graph shows the beginning and ending of the intersection. Red circles show the average point of the actions, and their size shows the relative population. The title shows the trial specifications and the number of participants that performed the trial). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

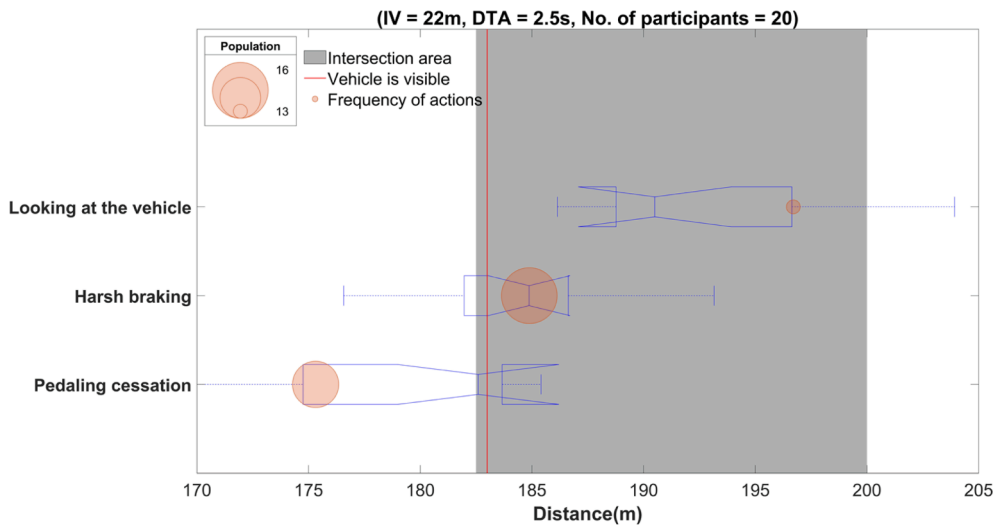


Fig. 5. Sequence of actions in Trial 2.

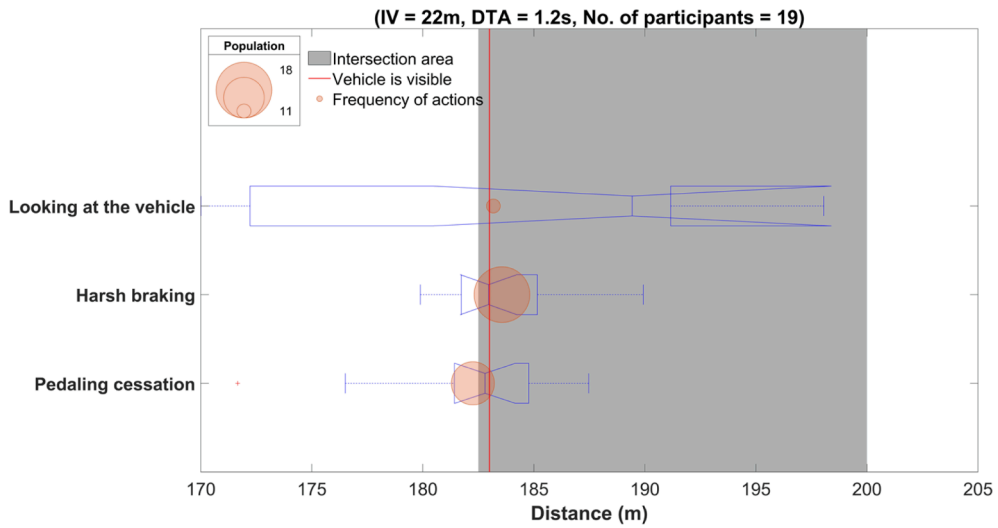


Fig. 6. Sequence of actions in Trial 5.

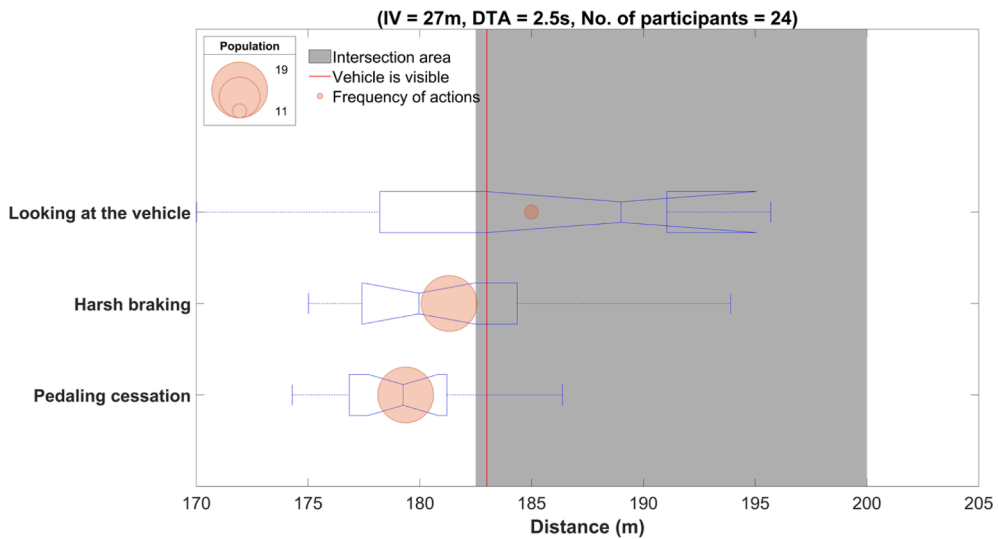


Fig. 7. Sequence of actions in Trial 7.

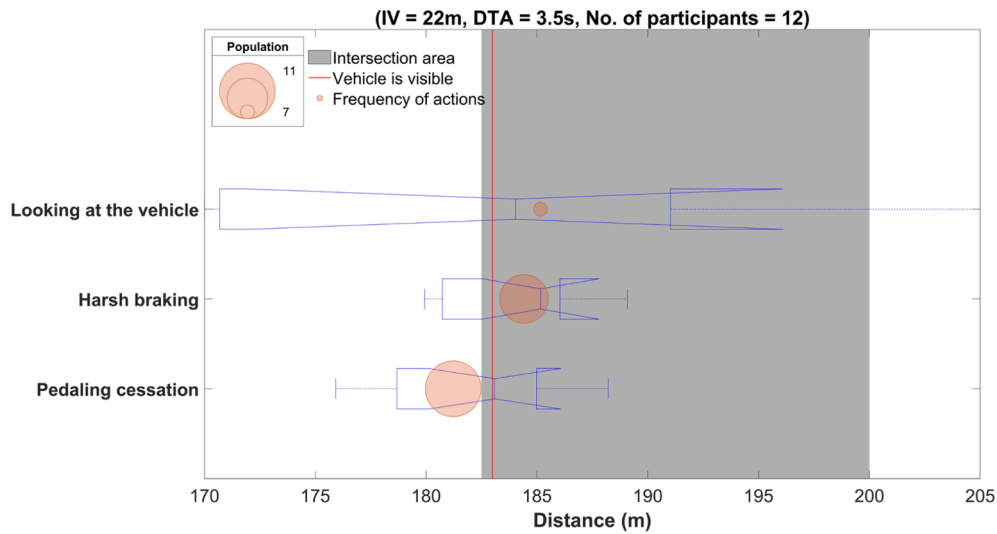


Fig. 8. Sequence of actions in Trial 10.

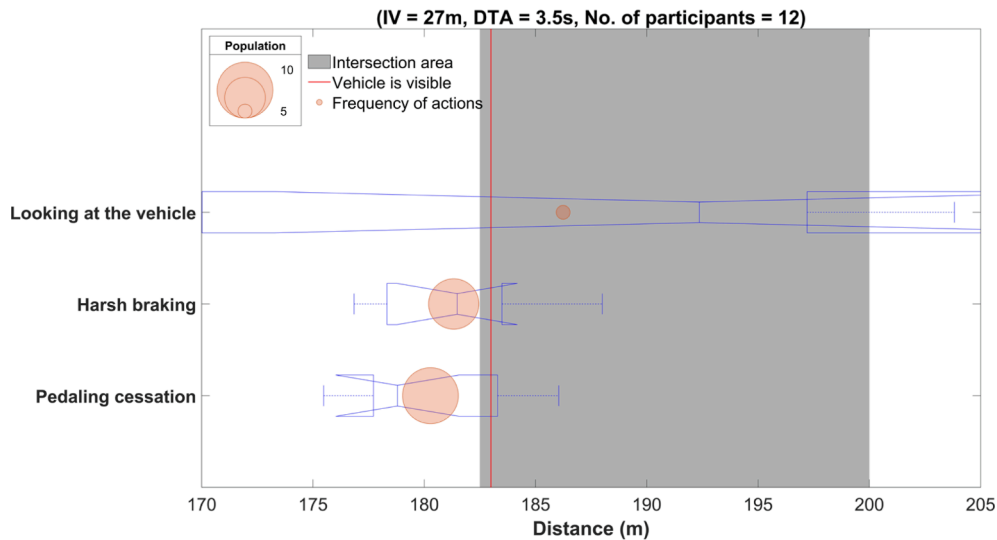


Fig. 9. Sequence of actions in Trial 11.

one trial in which the vehicle yields to the bicycle (trial 1, Fig. 4). In the five designated trials, the vehicle always drove through the intersection without yielding to the bicycle. In the trials when the vehicle yielded, the cyclists' sequence of actions was unaffected. For the same IV value, lowering the DTA value appears to lead to earlier braking and head turn towards the vehicle (see for example DTA = 1.2 s in Fig. 6, compared to DTA = 2.5 s and DTA = 3.5 s respectively in Figs. 5 and 8, for IV = 22 m; and DTA = 2.5 s in Fig. 7, compared to DTA = 3.5 s in Fig. 9, for IV = 27 m). When comparing trials with varying levels of visibility, while maintaining consistent DTA values braking tended to occur earlier when visibility was higher, as indicated in Fig. 5 and Fig. 7 (DTA = 2.5 s), and Fig. 8 and Fig. 9 (DTA = 3.5 s). In addition, in trials with no vehicle coming, the cyclists occasionally braked or looked for a car, but were more likely to stop pedaling. Since not all the participants completed all the trials due to motion sickness, and the trials were randomized, the population numbers differ in the Figures below.

To test the effect of the independent variables on cyclists' sequence of actions, cyclists' braking distance on longitudinal axes (longitudinal distance was measured from the beginning of the trial) was modeled, using linear mixed effect models. For the  $i^{th}$  participant, the linear expression may be written as equation (4), where  $\beta_{0,1,\dots,4}$  represents the intercept of the model and the fixed main effect, and  $\alpha_{0i}$  represents the

random effects.

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \dots + \alpha_{0i} + \varepsilon_i \quad (4)$$

The variables that were tested in the model consisted of DTA, IV, gender, age, surprise event (truck), order of trial, and cycling frequency. Some variables like gender, age, and cycling frequency (indicating cycling experience) were extracted from the questionnaire inputs. Table 2 shows the variables that were tested in the model.

Table 3 and Table 4 report the descriptive statistics of the variables that were tested in the models presented in this section and in Section 3.3.

The results of the braking distance model are shown in Table 5.

Among the variables that were tested in the model only DTA and IV affected the location where cyclists started braking. By increasing the DTA, cyclists braked later in distance and by increasing the IV, cyclists braked earlier. Equation (4) is written as equation (5), with the significant variables in the model and the grouping variable.

$$Y_i = \beta_0 + \beta_1 X_{DTAi} + \beta_2 X_{IVi} + \alpha_{participant i} + \varepsilon_i \quad (5)$$



**Table 2**  
Variables tested in the brake onset model (\*cyclists' braking distance is the dependent variable in the model).

Variable	Unit	Type	Description
1 Cyclists' braking distance*	m	Continuous	Braking distance assessed in the longitudinal axis
2 DTA	s	Continuous	Difference in time to arrival at the intersection
3 IV	m	Discrete	Intersection visibility
4 Age		Continuous	Age of the participant
5 Gender	Dummy	Categorical	Gender (male or female) of the participant
6 Surprise event	Dummy	Categorical	Trial with truck or without truck
7 Trial order		Continuous	The cardinal number indicating the order of trial
8 Cycling frequency	Nominal	Categorical	Participant's experience in cycling (1 occasional cyclist, 2 regular cyclist, 3 frequent cyclist, 4 daily cyclist)

**Table 3**  
Descriptive statistics of numeric variables.

Numeric variables	Mean	STD	Min	Max
Cyclists' braking distance (m)	182.77	4.12	175.02	193.9
Age	33.67	8.03	19	47
Trial order	5.96	3.63	1	12
Looking duration	296.14	186.6	41	748
Cycling frequency	2.84	0.82	1	4

**Table 4**  
Descriptive statistics of categorical variables.

Variable	Summary
Yielding decision	27% cyclists crossed first, and 73% vehicles crossed first
Gender	25% female, 75% male participants
Pedaling	22% were pedaling at the beginning of the intersection
Surprise event (truck)	One surprise event out of 12 trials

**Table 5**  
Summary of the estimation results for the braking onset model.

Fixed effects:	Estimate	Std. error	t value	Pr(> z )	5% CI	95% CI
Intercept	0.512	0.047	5.13	1.49e-15	2.74	5.93
DTA	0.108	0.054	2	0.048	0.008	0.42
IV	-0.205	0.172	-5.31	7.83e-07	-0.25	0.11
<b>Random effects:</b>	Variance	Std. dev.				
Participants	0.0218	0.148				

3.3. Cyclists' yielding decision

The mixed effect logistic regression evaluated the effect of independent variables on cyclists' yielding decisions. The data from 25 participants were used to develop the mixed effect logistic regression

**Table 6**  
Variables that were tested in the yielding decision model (\*yielding decision is the dependent variable in the model).

Variable	Unit	Type	Description
1 Yielding decision*	Dummy	Categorical	0 cyclist crossed first, 1 vehicle crossed first
2 DTA	s	Continuous	Difference in time to arrival at the intersection
3 IV	m	Discrete	Intersection visibility
4 Age		Continuous	Age of the participant
5 Gender	Dummy	Categorical	Gender (male or female) of the participant
6 Surprise event	Dummy	Categorical	Trial with truck or without truck
7 Trial order		Continuous	The cardinal number indicating the order of trial
8 Cycling frequency	Nominal	Categorical	Participant's experience in cycling (1 occasional cyclist, 2 regular cyclist, 3 frequent cyclist, 4 daily cyclist)
9 Pedaling	Dummy	Categorical	Pedaling or not at the beginning of the intersection
10 Looking duration	s	Continuous	Looking duration towards the oncoming vehicle

**Table 7**  
Summary of the model estimation results (only statistically significant results are shown).

Fixed effects:	Estimate	Std. error	Z value	Pr(> z )	5 % CI	95 % CI
Intercept	6.3	4.97	1.26	0.2	-3.44	16.06
DTA	-2.68	1.11	1.11	0.015	-4.86	-0.5
Looking duration	3.44	1.47	1.48	0.019	0.54	6.34
Pedaling	2.64	1.32	1.99	0.046	0.086	5.27
Random effects:	Variance	Std. dev.				
Participants	4.37	2.09				

model. For the  $i^{th}$  participant, the logistic linear expression may be written as equation (6), where  $\beta_{0,1,\dots,4}$  represents the intercept of the model and the fixed main effect, and  $\alpha_{0i}$  represents the random effects.

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \dots + \alpha_{0i} + \epsilon_i \quad (6)$$

The independent variables considered in the model are DTA, IV, gender, age, cycling frequency, trial order, pedaling, trial with truck, and looking duration. Table 6 shows the variables that were tested in the yielding decision model and their description.

Pedaling behavior is a binary variable indicating whether the cyclist was pedaling at the beginning of the intersection or not. Cyclists pedaling at the beginning of the intersection (edge of the curb, when entering the intersection) might have crossed the intersection first. The "looking duration" refers to the cumulative sum of timestamps when the cyclist turns their head by more than 15 degrees toward the approaching vehicle. This measurement is taken from the moment the cyclist enters the intersection until reaching the intersection points of trajectories.

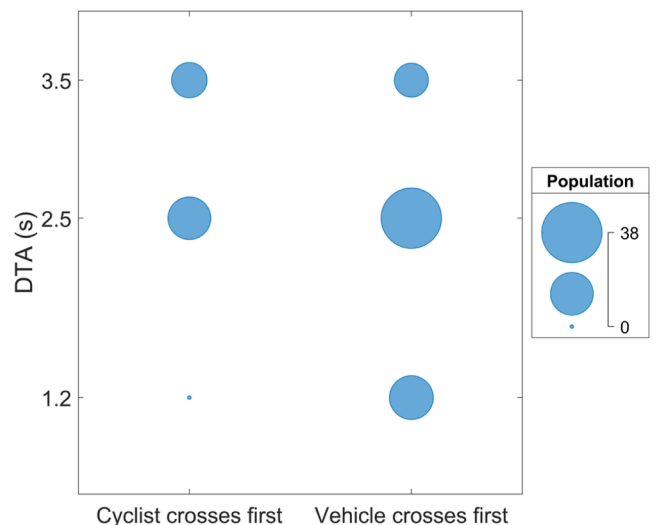


Fig. 10. Cyclist crossing decision with respect to changes in DTA.

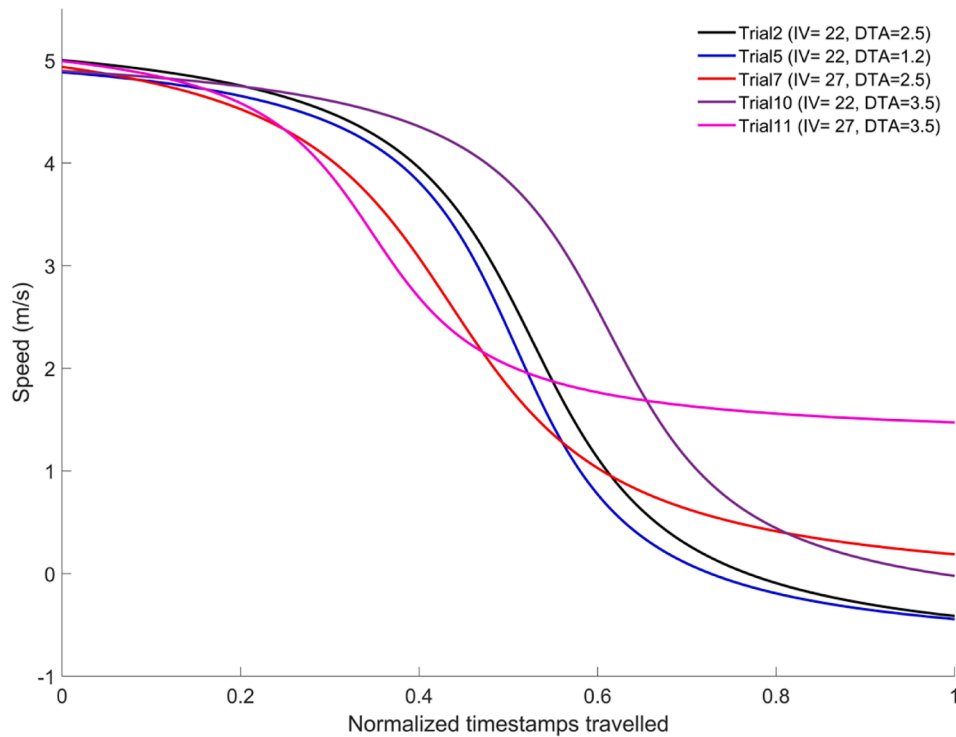


Fig. 11. Bicycles' average fitted speed profiles for the five main trials.

The full results of the mixed effect logistic regression are shown in Table 7. Based on Table 7, DTA, looking duration, and pedaling were significant in cyclists' decision to yield. It should be noted that the surprise event (interaction with a truck instead of a car) did not show any change in the cyclists' decision to yield. So, the vehicle type

(passenger car or truck) was not significant in the model. From the results of the model, cyclists looking longer at the vehicle had higher probability to yield for the vehicle. The influence of DTA can be understood from the bubble plots shown in Fig. 10. A larger share of cyclists decided to cross the intersection first when the DTA value was 2.5 s instead of 1.2 s. Finally, if the cyclists were pedaling before the beginning of the intersection, they were more likely to cross the intersection first.

Table 8  
Summary of fitting results.

Trial number	Maximum slope	R <sup>2</sup>
2	-8.21	0.906
5	-9.92	0.947
7	-7.60	0.941
10	-9.23	0.988
11	-6.48	0.984

Considering the modeling outputs in Table 7, Equation (6) can be rewritten as equation (7).

$$\text{Log}\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 X_{DTAi} + \beta_2 X_{lookingdurationi} + \beta_3 X_{pedalingi} + \alpha_{participant} + \varepsilon_i \quad (7)$$

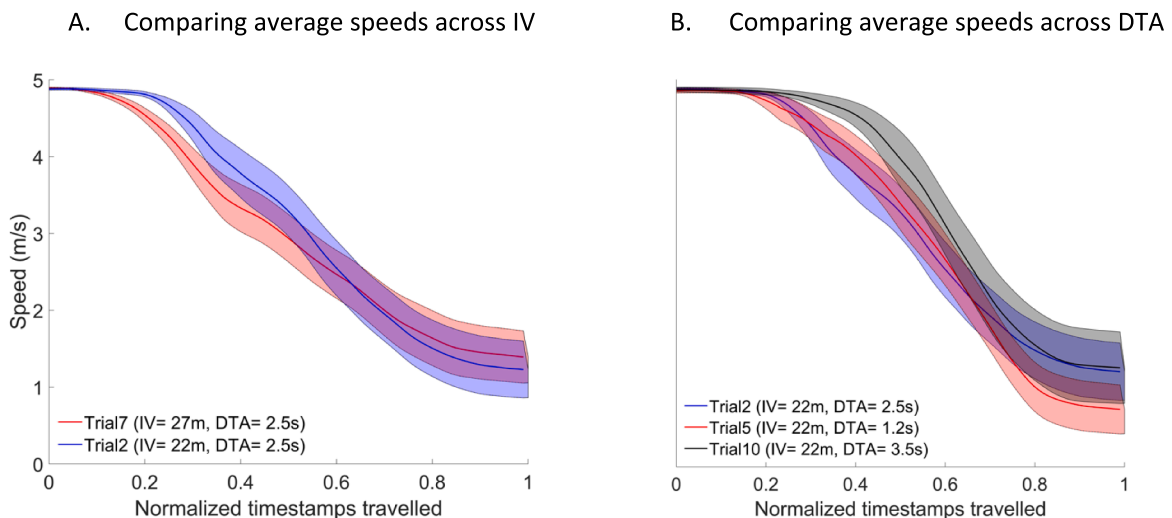


Fig. 12. Average speed profiles and confidence intervals: (A) a comparison between trials that have the same DTA and different IV and (B) a comparison between trials that have the same IV and different DTA.

3.4. Bicycle speed profiles

Equation (3) was fitted on all the successfully performed trials considered for the analyses (see Trials 2, 5, 7, 10, and 11 in Table 1). The time axis in Fig. 11 is normalized between 0 and 1, where 0 corresponds to 15 m from the intersection and 1 corresponds to the distance when they stopped braking. In the trials with the longer (27 m) IV, the participants reduced their speed sooner than in the trials with the shorter (22 m) IV (Fig. 11). Table 8 summarizes the modeling outputs for the main five trials. For the trials that had the same IV but different DTAs, the cyclists had the most severe braking profile at the lowest DTA value.

Fig. 12 compares the average speed profiles considering a single independent variable in each figure (while keeping constant the other independent variable) and their respective confidence intervals. We drew the two-sided confidence interval (confidence level value: 95%) for the variance to compare the average speed profiles.

3.5. Questionnaires

The results from the first questionnaire showed that the average MISC score at the end of the experiment was 3.18 (STD = 2.01) out of 10. As a result, by the end of the experiment, participants experienced a

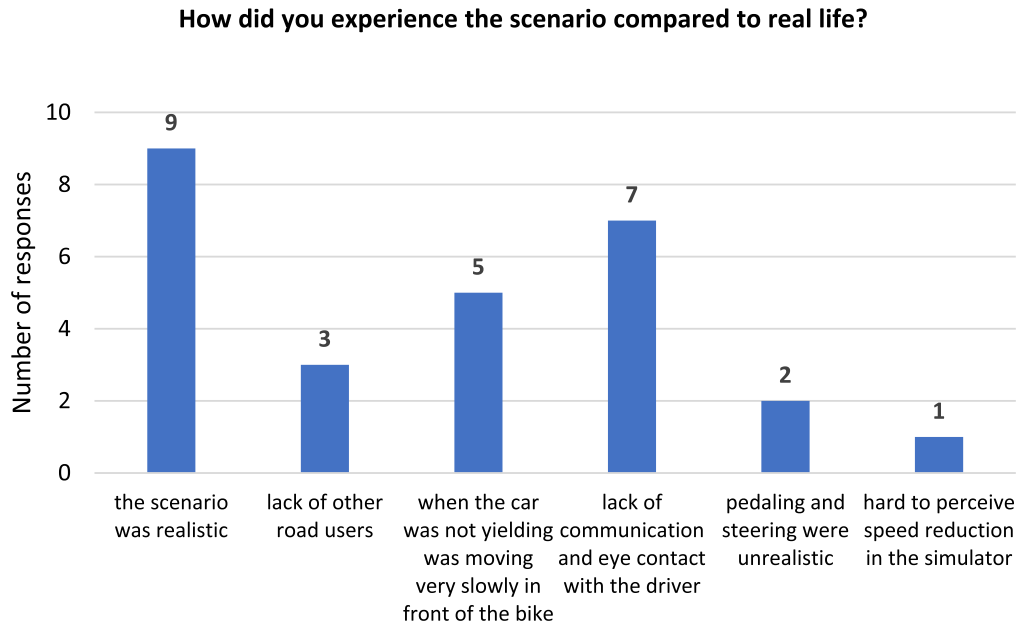


Fig. 13. Participants' responses about the simulator experiment (numbers above the bars show the number of responses out of 25 participants). Participants could provide multiple answers since it was an open question.

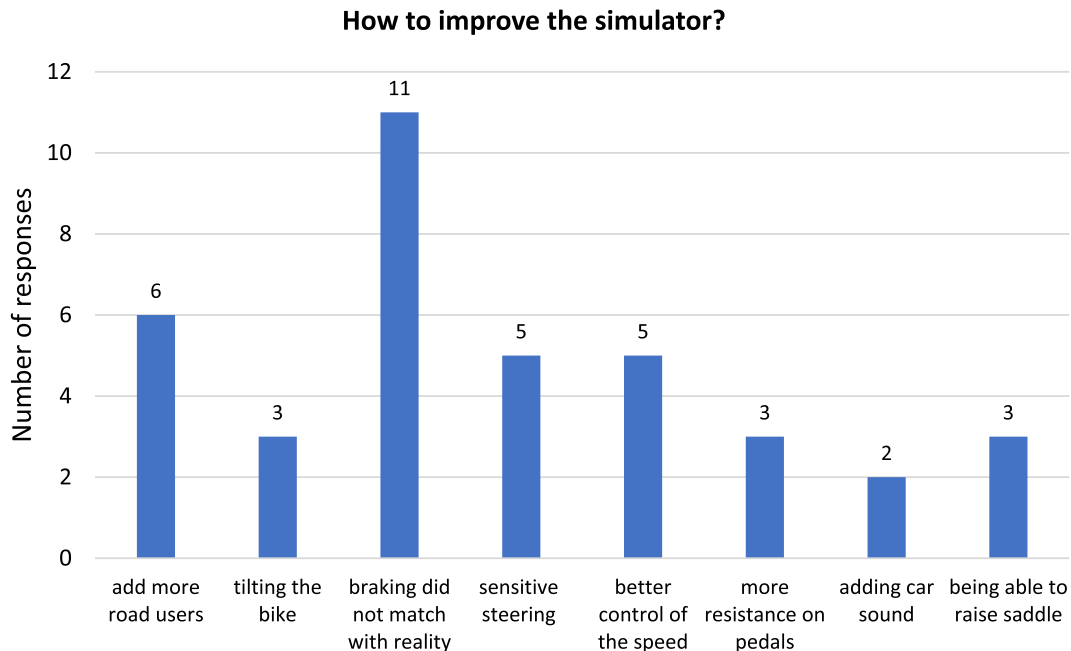


Fig. 14. Participants' suggestions for improving the simulator (numbers above the bars show the number of responses out of 25 participants). Participants could provide multiple answers since it was an open question.

level of motion sickness that they found relatively tolerable. Fig. 13 shows a summary of participants' responses to the open question, "How would you compare the scenario to real life?" This open question was an option for participants to express their experience in detail about the scenario. Notably, 36% of participants mentioned that the scenario was realistic, and 28 % of them said that a lack of communication and eye contact with the driver influenced their behavior to be more cautious when interacting with the vehicle (Fig. 13).

Fig. 14 shows participants' suggestions for improving the simulator. 44% of participants suggested that the braking and steering experience could be improved to match real cycling. Some participants complained about the low maximum speed; as mentioned in the methodology, it was chosen based on the average bicycle speed in the same intersection. Difficulty perceiving the speed in the bike simulator could explain why some participants felt the speed was low. There were also a few comments about adding more road users; however, our intention was to have a clean environment that would not complicate the interaction process. Other suggestions to improve the bike included: providing a degree of freedom in the lateral control, providing realistic sound for the approaching car, and raising the saddle. Addressing all these issues would help to create a better environment for test participants.

## 4. Discussion

### 4.1. Cyclists' behavioral patterns

Cyclists followed a consistent sequence of actions when interacting with the oncoming vehicle at the unsignalized intersection: stop pedaling, braking, and looking at the vehicle. In this study, a look to the vehicle was registered when the head yaw rate became larger than 15 degrees. However, the cyclists might have noticed the vehicle in their peripheral view before looking at it and decided to stop pedaling and braking, based on that information. Looking at the vehicle was probably used by the participants to closely observe the behavior of the vehicle and decide if yielding or not. A different sequence of actions was found in Trial 5 (IV = 22 m, DTA = 1.2 s), which was the most severe. Surprisingly, the participants looked before braking, the cyclists' actions were closer together, and the participants braked more often than they stopped pedaling. The different sequence of actions might be motivated by the need for the cyclist to brake harder to avoid the vehicle during an interaction, which was more critical due to the limited visibility and smaller DTA.

The independent variables IV and DTA influenced the response process. With increased IV, the cyclists' response process started earlier; they spotted the vehicle sooner, reacted to it earlier and, braking happened before the beginning of the intersection. On the other hand, lower DTA values caused the cyclists to decelerate more severely and to brake more often. Overall, cyclists usually stopped pedaling before the beginning of the intersection. The average place where they started braking differed in the different trials.

The information about cyclists' sequence of actions can be used by AVs to predict cyclists' behavior in different circumstances. Previous studies pointed out the importance of behavioral cues in predicting cyclist's intentions (Hemeren et al., 2014; Westerhuis & De Waard, 2017). In this study, we observed how behavioral cues (pedaling, head movement, and braking) changed in response to the independent variables. It is suggested that future work develop behavioral models of cyclists that include these cues to improve the models' predictive capabilities.

### 4.2. Cyclists' brake onset model

The outcomes of the brake onset model for cyclists indicated that the two independent variables significantly influenced the point at which cyclists initiated their braking maneuvers. Specifically, an increased level of visibility prompted cyclists to start braking earlier, a phenomenon attributable to their enhanced ability to detect the approaching

vehicle. Therefore, increasing visibility in unsignalized intersections can assist cyclists in detecting the threat in time to react safely. Conversely, an increase in the DTA resulted in cyclists initiating their braking maneuvers later in the distance. This delay can be attributed to the later arrival of the vehicle in scenarios with a greater DTA, which, in turn, led to cyclists perceiving and reacting to its presence later along their trajectory. The findings from this model substantiate the observations made in the sequence of action graphs (Figs. 4–9), emphasizing the significant influence of the independent variables on cyclists' decision-making and actions.

### 4.3. Cyclists' yielding decision

As shown in Table 7, three variables affected the cyclists' decision to cross. With increased DTA, more cyclists crossed the intersection first. This finding supports previous studies on vehicle interactions with vulnerable road users (Oxley et al., 2005; Velasco et al., 2021). The DTA values have been chosen on the positive side (cyclists arrived first at the intersection) to persuade cyclists to cross first. Based on field observations in the real intersection, cyclists crossed the intersection first more often at lower DTA values (Mohammadi et al., 2023). The simulator produced different results, potentially influenced by factors like the driverless nature of the interacting vehicle or specific conditions within the simulated environment. Nevertheless, DTA or its equivalent in distance, has been proven to be important in many studies that have investigated the interaction between vehicles and vulnerable road users (Lubbe & Rosén, 2014) and this study confirms the results of previous research. As the duration of cyclists' head turn towards the vehicle grew longer, their inclination to be the first to cross decreased. This heightened focus on the approaching vehicle might indicate cyclists exercising caution in response to uncertainty about the vehicle's actions, leading them to opt for yielding as a safety measure. The cyclists' pedaling behavior aligns with our initial anticipation, suggesting that those who wish to be the first to cross the intersection will continue pedaling. This observation corresponds with the results reported by Mohammadi et al. in their 2023 study, which established a connection between sustained pedaling and the intention to crossing the intersection first (Mohammadi et al., 2023).

The IV and the vehicle type were not significant in the model. However, the IV affected the braking distance (as described earlier) and cyclists' speed profile (which will be discussed in the next paragraph). The trial order was not also significant meaning that the sequence of trials was not important for the participants and participants' expectancy was reasonably low. Interacting with a truck did not affect the cyclists' decision to cross. This trial was the surprise event, at the end of the experiment—few participants performed it, due to motion sickness. Consequently, there was a small sample size (11) for this trial. Our preliminary results showed, however, that vehicle type does not change the cyclists' response process.

### 4.4. Cyclists' speed profiles

Results obtained from the average fitted speed profiles (Fig. 11) indicate that in trials with increased visibility, there was an earlier speed reduction observed for the cyclists. Based on Fig. 12.A, with higher IV, cyclists decreased their speed sooner, and the difference is evident in confidence intervals. This finding is in line with the results of the braking distance model, which showed that with higher IV, cyclists braked earlier (sooner speed reduction). Overall, with higher visibility, cyclists notice the vehicle sooner and react faster. Lack of proper visibility at crossings has been found to be a key contributing factor in crashes with vulnerable road users (González-Gómez & Castro, 2019; Narksri et al., 2019). So, providing more visibility at unsignalized intersections will help to have safer vehicle-cyclist interactions. Improving visibility at all the intersections that suffer from low visibility might not be feasible due to cost limitations. It is the AV's responsibility to be aware of the

situation they are approaching regarding visibility and to behave safely at crossings. AVs can recognize the environment they are approaching by their online navigating and information system (Yan et al., 2018).

By lowering DTA values (Fig. 12.B), harsher braking profiles were recorded (higher deceleration rates). These findings align with what was found in the sequence of actions. With lower DTA values, cyclists react to an unexpected encounter with the vehicle by braking harder.

#### 4.5. Motion sickness

Some participants felt motion sick at some point during the experiment due to full immersion (using VR headset), the lack of motion cues in the bike simulator, latency in visualization, and the sensory mismatch compared to real braking and steering. The experiment was stopped if there were mild symptoms of motion sickness during the test. Previous literature has reported that VR headsets induce more motion sickness than large screens (Mittelstaedt et al., 2018). There is a need to quantify the role of each mentioned issue in inducing motion sickness in bike simulators to further improve the simulators. Matvienko et al. evaluated the role of different countermeasures, like steering control and the moving environment, in reducing motion sickness in bike simulators (Matvienko et al., 2022). What is not mentioned in their study is braking performance, which we believe is a key factor in motion sickness. Others have tried to reduce motion sickness by using proper airflow, background music, and a pleasant scent (Keshavarz & Hecht, 2014). Creating a convincing and realistic cycling simulator may have a long way to go, but based on our experience, addressing the issues with visualization method, braking, and steering are the obvious starting points to developing an optimal bike simulator.

#### 4.6. Questionnaires

Based on the responses to the first open question (Fig. 13), many participants felt that the interaction scenario was realistic. One important point mentioned by the participants in the questionnaire was that they lacked eye contact and communication with the driver. This might have been the reason leading them to behave cautiously and yield more often to the vehicle. In fact, communication with the driver plays an important role in cyclists' decision-making (Hemeren et al., 2014) and the lack of communication between drivers and other road users should be considered for the design of AVs. Cyclists will eventually adapt to the presence of AVs in the future traffic system, but it takes a while to build trust in their safe performance (Vlakveld et al., 2020).

Most of the suggestions in response to the second open question, as anticipated, were related to the bike's braking, steering, and speed. The two important issues they mentioned were an unreal braking experience and sensitive steering. The braking issue was due to the lack of motion cues in the simulator, which made some participants feel dizzy. The maximum speed of the bike was set to be constant to control the time to arrival at the intersection (DTA).

#### 4.7. Limitations and future work

The first limitation of the experiment was that it had fewer participants than expected due to the pandemic. The experiment was carried out during the spring of 2021, and people were still concerned about infection, so the participation rate was lower than in pre-pandemic times. In the end, reasonable number (27) of participants was tested but having more data in the future will help drawing more sound conclusions. The next limitation of the experiment refers back to the unavoidable issues with the simulator. As mentioned by some participants in the questionnaires, the braking, steering, and speed control did not accurately replicate a real cycling experience (Figs. 13 and 14). This mismatch caused participants to feel motion sick at different levels during the experiment. Attempts were made to preserve the data by stopping the experiment once the motion sickness symptoms appeared,

but the resulting data loss for the missed trials was unfortunate. The bike simulator had a fixed saddle height, limiting us to testing people taller than 185 cm. In addition, given that the bike simulator was static, there was no possibility of leaning when steering. In summary, developing a bike simulator that could overcome the above limitations may help to recreate a more realistic scenario for interacting with vehicles. Presently, we do not know the extent to which our results were affected by the technical limitations of the riding simulator.

As mentioned in previous studies, communication and eye contact with the driver play an important role in cyclist-vehicle interactions (Guéguen et al., 2016; Hemeren et al., 2014). In this study, the interacting vehicle clearly had no driver inside for cyclists to communicate with. For future work we suggest using external HMI (Human-Machine Interface) on the vehicle as a substitute for the driver and testing the communication methods with the cyclists at crossings.

There is a need to evaluate the ecological validity of the bike simulator and investigate to what extent the results from the bike simulator match reality. Further analysis should be done to compare the results from field data and the bike simulator data. In addition, there is also a need to observe the interaction process from the driver's perspective by redoing the experiment, possibly using a driving simulator that interacts with a simulated cyclist.

## 5. Conclusion

This study investigated the cyclists' response process when deciding whether to cross ahead of a vehicle at an unsignalized intersection in a riding simulator. Two independent variables, DTA and IV, were manipulated in this experiment.

The cyclists' response process was consistent in all trials except one. Cyclists approached the intersection by stopping pedaling, braking, and looking at the approaching vehicle. Based on the mixed effect model, DTA, looking duration, and pedaling significantly affected cyclists' yielding decision. Although visibility did not significantly affect the yielding decision, it had a significant influence on the braking onset decision, together with DTA. With higher visibility, cyclists reacted sooner to the presence of the car. Providing more visibility at unsignalized intersections may lead to less severe encounters between road users. Lowering the DTA values resulted in a lower probability of cyclists crossing first and harsher braking profiles for the bike. Therefore, the model's outcome can help find DTA thresholds at which an AV can cross the intersection safely when interacting with a cyclist.

Another important finding of this study is that participants highlighted the lack of communication and eye contact with the driver as one of the main differences with daily cycling. The lack of communication with the driver will also be a characteristic trait of the interaction between cyclists in future driverless vehicles. Particular attention should be placed on ensuring that the lack of communication would not undermine cycling safety. Some surrogate communication may be needed, not only to grant safety but also to make the introduction of automated vehicles more comfortable and safer.

The bike simulator used for this study may be improved for future studies by adding cycling motion cues, a better graphical interface, and a lateral degree of freedom. Overcoming the limitations in the bike simulators can be beneficial for recreating critical cyclists' interaction scenarios in the virtual environment and, most of all, to avoid motion sickness.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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