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How do cyclists interact with motorized vehicles at unsignalized intersections? Modeling cyclists' yielding behavior using naturalistic data

Ali Mohammadi *, Giulio Bianchi Piccinini, Marco Dozza

Department of Mechanics and Maritime Sciences, Chalmers University of Technology

A R T I C L E I N F O

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A B S T R A C T

When a cyclist's path intersects with that of a motorized vehicle at an unsignalized intersection, serious conflicts may happen. In recent years, the number of cyclist fatalities in this conflict scenario has held steady, while the number in many other traffic scenarios has been decreasing. There is, therefore, a need to further study this conflict scenario in order to make it safer. With the advent of automated vehicles, threat assessment algorithms able to predict cyclists' (other road users') behavior will be increasingly important to ensure safety.

To date, the handful of studies that have modeled the vehicle-cyclist interaction at unsignalized intersections have used kinematics (speed and location) alone without using cyclists' behavioral cues, such as pedaling or gesturing. As a result, we do not know whether non-verbal communication (e.g., from behavioral cues) could improve model predictions.

In this paper, we propose a quantitative model based on naturalistic data, which uses additional non-verbal information to predict cyclists' crossing intentions at unsignalized intersections. Interaction events were extracted from a trajectory dataset and enriched by adding cyclists' behavioral cues obtained from sensors. Both kinematics and cyclists' behavioral cues (e.g., pedaling and head movement), were found to be statistically significant for predicting the cyclist's yielding behavior. This research shows that adding information about the cyclists' behavioral cues to the threat assessment algorithms of active safety systems and automated vehicles will improve safety.

1. Introduction

Public agencies promote cycling as an active mode of transport because of numerous direct and indirect benefits for both the cyclist and society (Edwards and Mason, 2014; Pucher and Buehler, 2017). In recent years, cycling has grown in popularity as a mode of transport (Pucher and Buehler, 2017). Unfortunately, with the higher exposure rate of cyclists in mixed traffic, more conflicts take place. European crash data shows that the cyclists' share of road traffic fatalities is increasing year by year (European Road Safety Observatory, 2018). Since they do not have a metal shield around them for protection, cyclists are considered vulnerable road users, so their safety is a priority for all transport system stakeholders. Most of the conflicts between cyclists and motorized vehicles happen at crossings when the two road users share the road, and their trajectories intersect (Bjorklund, 2005). These scenarios are particularly critical at unsignalized intersections, which operate based on priority rules for road users and require communication and agreement between the cyclist and the driver. In these intersections, the driver usually allows the cyclist to pass first (Bjorklund, 2005); however, Svensson and Pauna show that in 42 % of the cases in Sweden, drivers do not yield to cyclists (Svensson and Pauna, 2010). The way that the involved road users interact and communicate intent in these scenarios must be understood and modeled before it can be employed by automated vehicles (AVs) and safety systems.

Few studies so far have focused on how automated vehicles should behave and interact when encountering cyclists [5, 6]. Although simulations show that with a 100 % penetration rate of AVs, conflicts between AVs and cyclists decrease, AVs should still be trained to behave safely when interacting with cyclists in mixed traffic (Tafidis et al., 2019). The AVs should be able to process explicit and implicit communication from the cyclist and respond appropriately. Road users use explicit communication to convey a message deliberately, while implicit communication is always present even if the road user does not notice it (Miller et al., 2022). Further, AVs move forward based on continuous sensing, prediction, and action. Hence, AVs need to accurately predict other road users' behavior to plan their path safely, which

* Corresponding author.
E-mail addresses: ali.mohammadi@chalmers.se (A. Mohammadi), gbp@build.aau.dk (G. Bianchi Piccinini), Marco.dozza@chalmers.se (M. Dozza).

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can be accomplished with prediction models. At the same time, developing active safety systems for conventional vehicles is also essential to have safer traffic for vulnerable road users. In recent years some active safety systems like automated emergency braking (AEB), forward collision warning (FCW), and automated emergency steering (AES) have been developed to deal with the conflicts between motorized vehicles and cyclists at intersections. The performance of these safety systems is assessed by the European new car assessment program (Euro NCAP). The safety systems activate based on an algorithm to predict a threat. However, there are few studies addressing the development of behavioral models for predicting cyclists' intention at crossing scenarios. Developing predictive models for AVs and safety systems of the interaction between cyclists and motorized vehicles would require describing cyclists' behavior and how they communicate their intent (to yield or not).

Silvano et al. (2016) developed a logistical model to predict who will yield at the intersection based on kinematic (speed and location) information. Theirs was the first study to model the vehicle-cyclist interaction; unfortunately, they lacked accurate kinematic information. The second work is from Bella and Silvestri (2018), who performed a descriptive analysis of the effect of different infrastructure designs on driver control. Using a driving simulator, they assessed the efficacy of different safety countermeasures (like pavement color and raised islands) at reducing drivers' speed when drivers interacted with a cyclist at the crossing. They did not model the cyclist-vehicle interaction. Boda et al. (2020) proposed a computational model to predict driver behavior. As input for their model, they used two visual cues: optical looming control and projected post-encroachment time. The model mainly predicts when drivers initiate braking and how long they brake. They used test track data to fit the model, and for its validation, they used simulator data. On the test track, the cyclist was a dummy moving in front of the vehicle, so the dynamic of the interaction might not be very realistic. The study's focus was exclusively on how the driver responded to an oncoming cyclist. In another study, Velasco et al. (2021) used virtual reality headsets. They showed videos of oncoming vehicles to participants (who were cycling) and observed which factors were relevant for them as they crossed the intersection. They concluded that the distance between the car and the bicycle and which vehicle had the right of way were the primary factors affecting the cyclist's intention to cross the intersection. These studies indicate that kinematics play an important role in cyclist-vehicle interaction. In this study, we aimed to overcome the limitations of these works by collecting naturalistic data and investigating the role of additional visual information on cyclist-vehicle interactions at unsignalized intersections.

There is growing evidence that by incorporating visual information about interacting road users in computational models, we can predict their behavior more accurately and rapidly. Road users use visual information about each other's behavior as cues, to interact with other road users. Informal communication between road users, including eye contact, hand gestures, and body movement, can effectively indicate intent, informing others about imminent actions. These cues can be helpful for predicting road users' intent. In fact, many of the efforts in this area are related to pedestrian-vehicle interactions, and very few studies observe the role of cyclists' behavioral cues in cyclist-vehicle interactions (Mahadevan et al., 2018). In one such study in 2014, Hemeren et al. (2014) observed whether participants could predict cyclists' behavior at crossing scenarios using non-verbal information. They showed participants videos of bikes crossing an intersection and asked them about the visual cues they used to predict cyclists' future paths. They concluded that speed, head turn, and position (cyclist is leaning or sitting up straight) are the most critical cues for predicting cyclists' paths. Other researchers have also tried to find the connection between visual cues and cyclists' intentions; Abadi and Goncharenko (2022) used neural networks to try to find the relation between cyclists' head orientation and crossing intention. Westerhuis and De Waard (2017) tried to link the direction of maneuvers at an intersection to cyclists' visual cues. They showed videos of moving cyclists to participants and paused the videos at a certain moment, and asked the participants which direction the cyclist would go. Head movement and cyclist speed were found to be important in predicting cyclists' future paths. The aforementioned studies emphasize the importance of visual cues for predicting cyclists' intent in the urban environment; however, they do not quantify the relation between visual cues and intent. This study focuses on predicting cyclists' intention to cross at an unsignalized intersection using naturalistic data. Previous works just considered kinematic information to model cyclist-vehicle interaction. In this paper, we combine both kinematic information and cyclists' visual cues in order to determine how important the visual cues are to improving the prediction of cyclists' intentions.

To investigate interactions between cyclists and motorized vehicles, we extracted conflicts between road users from naturalistic field data. To measure the safety level of observed interactions, we used surrogate measures of safety (SMoS), which are widely used in the traffic safety domain. These proactive safety measures are used for conflict interactions (Wang et al., 2021), which are more frequent than crashes. The SMoSs' post-encroachment time (PET) and projected PET were chosen to measure the safety level of the interaction events in this study. PET refers to the actual time lapse between the first road user leaving the conflict zone and the second road user entering the conflict zone (Allen et al., 1978). The projected PET is an estimation or projection of PET (Boda et al., 2020). Its value is calculated by dividing the distance between the two road users when the first road user exits the conflict zone by the speed of the second road user. The projected value thus assumes that the speed of the second road user is constant from that point in time.

This study aims to propose a quantitative model to predict cyclists' intention to cross an intersection using naturalistic data. Our main objectives were to determine 1) what visual cues are used by cyclists to communicate to drivers their intent to cross and 2) the extent to which these cues may help predict whether a cyclist approaching an intersection will yield or pass through.

2. Methodology

In this study, we examined how cyclists negotiate an unsignalized intersection with motorized vehicle drivers and identified which factors help predict who is going to yield. For reference, note that Swedish traffic rules state that motorized vehicles must give way to cyclists at unsignalized intersections, and cyclists should pay attention to the surrounding vehicles and cross the intersection carefully.

2.1. Data collection

The data for this study come from an unsignalized urban intersection in Gothenburg, Sweden (GPS coordinates: 57°42′31.1″N, 11°56′22.9″E). Stereovision and an AI-based sensor from Viscando (VISCANDO) mounted at the corner of the intersection recorded video of trajectories of all road users for 14 days in June 2019. The data for each day were collected from 6:00 to 18:00. The defined road user categories were pedestrians, cyclists, vehicles, and heavy vehicles; trajectory data comprised positions, speeds, and headings (recorded at a frequency of 20 Hz). We searched for the objects labeled 'cyclists' and 'vehicles' in the trajectory dataset and only used events which included a single car and a single bicycle approaching the intersection (and no other road user present). An interaction event can be defined as occurring when two road users share the road; they may try to communicate with each other and probe the other's intent to follow a safe and comfortable path (Thalya et al., 2020). We used this definition to observe whether there was a possible communication or negotiation of intent between the two road users in the correspondent videos. The average lengths of the trajectories for bicycles and vehicles were about 23 m and 16 m, respectively, working backwards from the trajectories' intersection point. Fig. 1.a shows an example of the cyclist and vehicle trajectories.

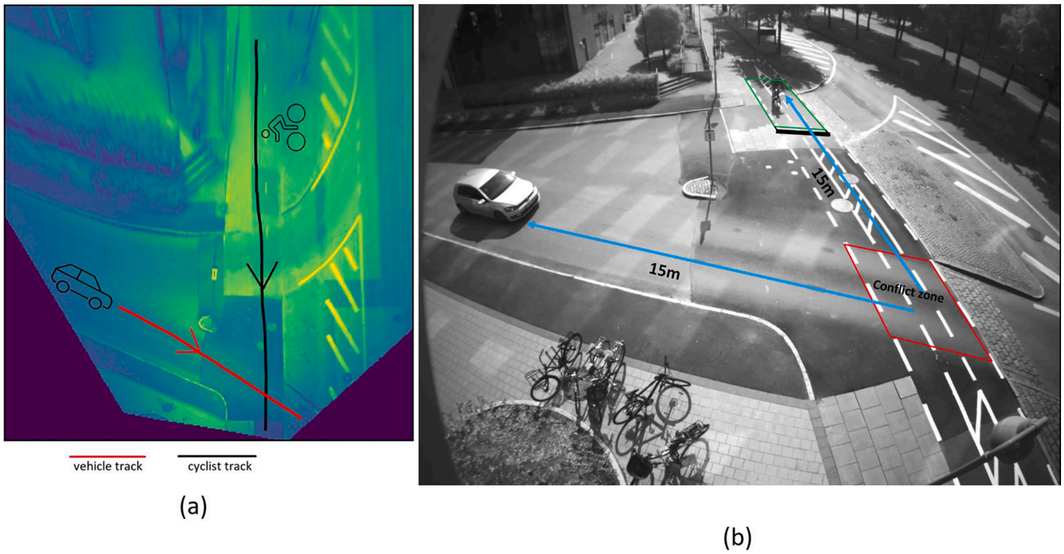

Fig. 1. Studied intersection: (a) layout of the intersection and the trajectories of the car and bicycle, (b) intersection view from the mounted Viscando sensor illustrating the defined areas for determining the variables affecting the car driver's decision to pass. The green box represents the area for determining the visual parameters, the black line shows the approximate area for decision making, and the red box delineates the conflict zone. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.2. Interaction events

The procedure to find and select interaction events (i.e., occurrences when a cyclist and a motorized vehicle approach the intersection at the same time) from the anonymized videos was based on the difference in time to arrival (DTA) at the intersection for the involved road users (Fig. 1b). DTA is a measurement to assess which road user arrived sooner at the intersection and by how much. We defined equal distances of 15 m to the intersection point of trajectories both in the cyclist's and vehicle's path, from the point where the cyclist enters the intersection (edge of the curb). The time difference between the interacting road users reaching this 15 m distance is calculated as the DTA. DTA is positive when the car arrives first at the intersection and negative when the bicycle arrives first. Fig. 1b shows the observed intersection and the distances for calculating DTA from the mounted Viscando sensor's perspective.

We defined a threshold for the DTA of $\pm$ 7 s based on a preliminary visual assessment of the video events. An algorithm was written to find the interaction events in the trajectory dataset that were below this threshold and then the corresponding videos were manually checked to ensure that the selection of events was correct. We extracted the kinematic information for the involved road users from the trajectory dataset and annotated the correspondent videos to record additional information. Fig. 2 shows the process of finding and registering interaction events. In total, there were 105 confirmed interaction events between passenger cars and cyclists. We defined all the variables extracted for each interaction event, which are reported in Table 1; the first part of the table contains the variables extracted from the trajectory data set, and the second part describes the variables acquired from the video annotation.

An ID was assigned to each interaction event (Table 1), and each involved cyclist and motorized vehicle. The involved road users' kinematic information includes their speeds. Because visual information about the cyclists could be relevant to understanding their behavior during the interaction, we chose to code three variables that could indicate implicit communication between the cyclist and the motorized vehicle: whether they were pedaling, looking toward the approaching vehicle, and making any hand gestures (e.g., as a sign to let the vehicle cross first or to thank the driver). We registered these variables as time series, meaning that the variables were continuously annotated (categorically for each time stamp) during the whole trajectory of each cyclist (Table 1).

For each interaction event, the PET and projected PET were calculated, and the DTA was recorded. The decision to yield was recorded as a binary variable: 0 if the car driver yielded and 1 if the cyclist yielded. Cyclist gender was categorized as either male or female. A categorical variable was defined with three age categories: adults, elderly, and children (Table 1). Weather condition was a binary variable that indicated whether it was rainy during the event. A variable was coded for lighting conditions: day or night (Table 1). The interactions were assigned a severity level from 0 (low severity) to 4 (crash), using Hyden's "safety pyramid" as inspiration (Hyden, 1987). We coded cyclists wearing a helmet or not as a variable. We also coded a variable to describe whether the bike was an e-bike or a normal bike (Table 1).

2.3. Decision point

Visual observation of the interaction events and cyclists' speed profiles indicates that cyclists started to either accelerate or brake about 8 m before the trajectories' intersection point. Therefore, we used this distance as the decision point for the cyclists and sought to determine the occurrence of cyclists' visual cues (pedaling, looking at the motorized vehicle, and hand gesture) before this point. The model also aims to predict the decision to yield (based on these cues) before the cyclist arrives at the decision point. The area for determining the cyclist's visual

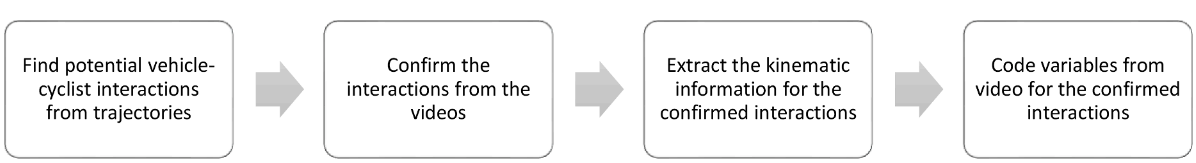

Fig. 2. Process of finding and coding interaction events.

Table 1
Variable extracted for each interaction event.

	Variable	Unit	Data type	Description
Information acquired from the trajectory dataset				
1	Event ID		Numeric	Unique identification for the event
2	Cyclist ID		Numeric	Unique identification for the cyclist
3	Cyclist speed	m/s	Time series	Cyclist speed
4	Vehicle ID		Numeric	Unique identification for the vehicle
5	Vehicle speed	m/s	time series	Vehicle speed
Information acquired from the video annotation				
6	Cyclist pedaling	dummy	time series	0 for the pedaling time stamps and 1 for not pedaling time stamps
7	Cyclist's head movement	dummy	time series	0 for the looking ahead timestamps and 1 for looking to the vehicle time stamps
8	Cyclist's hand gesture	dummy	time series	0 for not having hand gesture timestamps and 1 for having hand gesture time stamps
9	PET	sec	Numeric	Post encroachment time
10	Projected PET	sec	Numeric	Projected post encroachment time
11	DTA	sec	Numeric	Difference in time to arrival to the intersection
12	Yielding Decision	dummy	Categorical	0 for cyclists pass first, and 1 for vehicles pass first
13	Gender	dummy	Categorical	0 male, 1 female
14	Age	categorical	Categorical	0 adult, 1 child, 2 elderly
15	Weather condition	dummy	Categorical	0 without rain, 1 rainy
16	Lighting condition	dummy	Categorical	0 day, 1 night
17	Conflict severity	categorical	Categorical	0 encounters, 1 potential conflicts, 2 slight conflicts, 3 serious conflicts
18	Wearing helmet	dummy	Categorical	0 wearing helmet, 1 not wearing helmet
19	Bike type	dummy	Categorical	0 normal bike, 1 e-bike

information is shown in Fig. 1b. These visual parameters are determined as dummy variables when they occur before the decision point (between 8 and 12 m before the intersection point). We extracted the cyclist's and vehicle's speeds from the first moment that they were visible to each other (19 and 15 m from the intersection point for the bike and vehicle, respectively). We held these speeds constant in the model since the road users' first impression of the other's speed would affect their behavior.

2.4. Inter- and intra-rater reliability for annotations

We assessed inter-rater reliability, to measure the agreement between the different analysts coding the videos, and intra-rater reliability, to measure the extent to which the annotations were consistent when a single analyst repeated the procedure. Two analysts annotated the videos for the chosen interactions. Cohen's kappa method was used as an indicator to express the level of agreement for the intra- and inter-rater reliability measures (Gisev et al., 2013). The range of this indicator is between 0 and 1; 0 means no agreement, and 1 indicates a perfect agreement between raters. Previous research has pointed out that differences in raters' codes for 10–25 % of the data is typical for inter-rater reliability (O'Connor and Joffe, 2020). A value of 0.81–1 is considered an almost perfect agreement between raters in the literature. The formula for Cohen's kappa is calculated as:

$$\mathrm{K} = \frac{(P_0 - P_e)}{(1 - P_e)} \tag{1}$$

Where:
P_0 = relative observed agreement among raters
P_e = hypothetical probability of chance agreement

2.5. Modeling framework

In order to develop a model that could predict which road user will yield at the intersection given the defined parameters, we used generalized linear models (GLMs) to relate the independent variables to the outcome. GLMs generalize linear regression by relating the linear model to the response variable with a link function. These models allow the magnitude of the variance of each measurement to be a function of its predicted value (Myers and Montgomery, 1997). This modeling framework unifies different types of statistical models like binomial regression, Poisson regression, and classical linear regression models.

We chose a logit model to predict which road user will yield at the intersection. A binary logit model gives the probability of yielding or not for the involved road users.

$$P = \frac{\exp(a + b_1x_1 + b_2x_2 + b_3x_3 + \cdots)}{1 + \exp(a + b_1x_1 + b_2x_2 + b_3x_3 + \cdots)} \tag{2}$$

Where,
P = the probability that a case is in one category
b_1, b_2, b_3 = vector of parameters to be estimated
x_1, x_2, x_3 = independent variables affecting the decision to yield
a = intercept

2.6. Oversampling

The SMOTE (Synthetic Minority Oversampling Technique) was used to balance the response variable in the model (Chawla et al., 2002). This method avoids the model's poor performance on the minority class of the response variable, which in our model is the yielding decision. In imbalanced datasets, the classification models ignore the minority class and thus are not very effective at predicting it. The SMOTE method creates as many synthetic cases for the minority class as required to balance the dataset.

2.7. Validation

The leave-one-out cross-validation method (LOOCV) determined the model performance. This method is often used when the sample size is small, and it is not efficient to divide the dataset into train and test parts. For a sample size n, LOOCV creates n-1 models; in each model, one of the observations is left out to be used for validation, and the n-1 observations train the model (Arlot and Celisse, 2010). This process repeats n times, and in each iteration one of the observations is left out for the validation. The average accuracy of all created models is reported as the model performance.

3. Results

3.1. Data description

In total, 105 interaction events were extracted for analysis and modeling; among them, 35 % of the cyclists were women, and 65 % were men. In 65 % of the events, the bike passed through the intersection first, and in 35 % of cases, the vehicle passed through the intersection first. In 66 % of cases, cyclists had a helmet. Cyclists were pedaling before the decision point in 65 % of cases. In 30 % of cases, cyclists were looking at the approaching vehicle before the decision point. There were two e-bikes among the observed cases, and seven elderly cyclists. Cyclists waved a hand at the approaching vehicle in three cases. Descriptive statistics of numeric variables that were tested in the model are shown in Table 2.

3.2. Safety measures

Fig. 3. a–d show the distributions of PET, projected PET, DTA, and severity levels. The average projected PET values are higher than their

Table 2
Descriptive statistics of numeric variables (DTA: the difference in time to arrival at the intersection, PET: post-encroachment time).

Numeric variables	Bike initial speed (m/s)	Vehicle initial speed (m/s)	DTA* (s)	PET* (s)	Projected PET (s)
Mean	3.98	3.28	1.94	2.6	4.31
STD	1.06	1.15	2.27	0.93	2.77
Min	0.42	0.26	−2.56	0.95	0.86
Max	7.58	6.11	8.83	5.87	12.5

respective PET values. In projected PET, we kept the speed of the second road user constant for the calculation, although the second road user actually slowed down in the intersection. Based on Table 2 and the PET distribution in Fig. 3.a, the average PET is 2.6 s.

Most of the DTA values are positive, which shows that most interactions happened when the car arrived first at the intersection. When the cyclists arrived first at the intersection, they usually passed through the intersection without being influenced by the vehicle. Fig. 3d shows the distribution of the interaction's severity levels.

Table 3 shows the variables that were tested in the model. Among the variables that we recorded (Table 1), weather and light conditions were not considered because all events happened during the day and without rain. It is worth noticing that PET, interaction severity level, and projected PET were also coded for each event. However, we did not include them in the model because they cannot be used to predict the yielding decision; in fact, these variables are processed once the yielding decision has already been made.

3.3. Modeling output

Table 4 shows the estimation results for yielding probability for the variables that were statistically significant in the model. As noted, since the number of cyclists' yielding cases were less than half that of the vehicles' yielding cases, we used SMOTE to balance the response variable by oversampling. The number of observations increased to 136, with an equal number of yielding cases for cyclists and drivers.

As shown in Table 4, the variables significantly affecting the decision to yield are the cyclist's initial speed, vehicle's initial speed, DTA, pedaling (or not), and looking towards the motorized vehicle (or not). With every unit increase in cyclist's speed, the log odds of the cyclist

Table 3
Factors chosen for the model.

	Variable	Unit	Type	Description
1	Cyclist speed	m/s	numeric	Cyclist's initial speed
2	Vehicle speed	m/s	numeric	Vehicle's initial speed
3	DTA	sec	numeric	Time difference to arrival to the intersection
4	Gender	dummy	Categorical	0 men, 1 woman,
5	Age	dummy	Categorical	0 for adult, 1 child, 2 elderly
6	Bike type	dummy	Categorical	0 normal bike, 1 e-bike
7	Wearing a helmet	dummy	Categorical	0 wearing helmet, 1 not wearing helmet
8	Looking or not	dummy	Categorical	Looking to the vehicle before the decision point
9	Pedaling or not	dummy	Categorical	Pedaling or not before the decision point
10	Hand gesture or not	dummy	Categorical	Hand gesture before the decision point

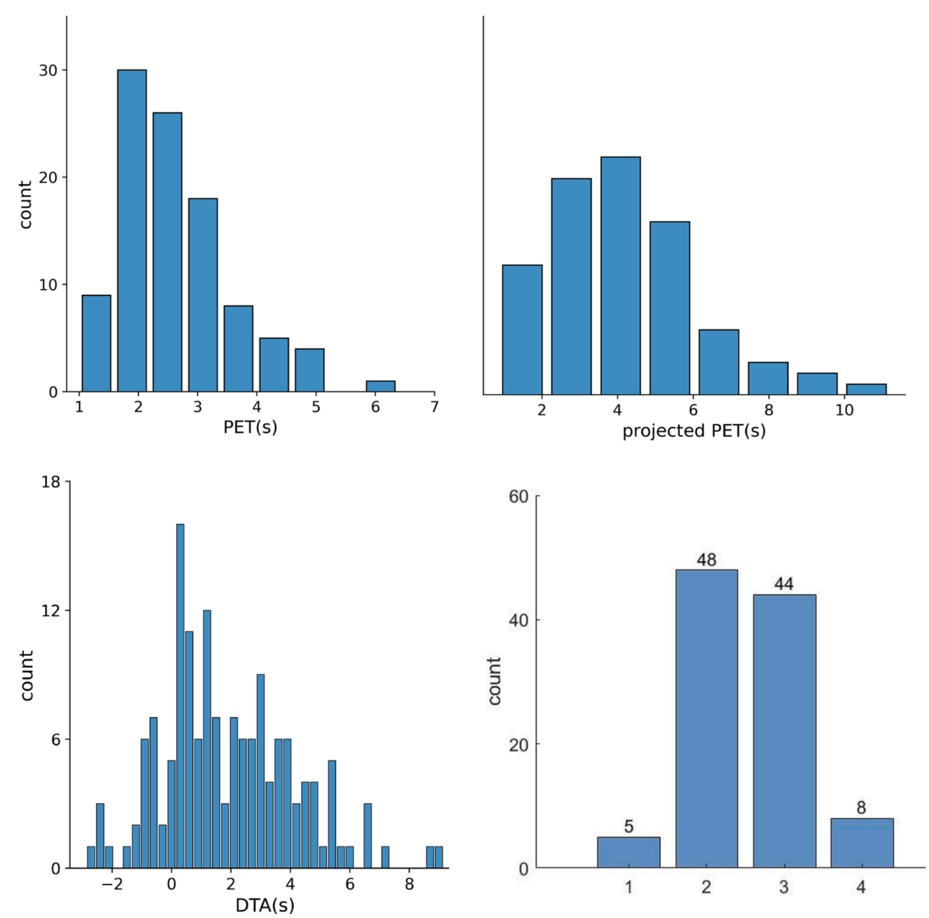

Fig. 3. Distribution of PET, projected PET, and DTA, and severity levels.

Table 4
Summary of model estimation results.

Variables	Coefficients	std err	Z score	*p*-value	lower bound (0.025)	Upper bound (0.975)
Intercept	−4.3523	1.474	−2.953	0.003	−7.241	−1.464
Bike speed	−4.7794	2.041	−2.342	0.019	−8.779	−0.780
Vehicle speed	9.4198	1.910	4.932	p < 0.001	5.676	13.163
DTA	5.5818	1.194	4.675	p < 0.001	3.242	7.922
Pedaling or not	1.1403	0.551	2.068	0.039	0.060	2.221
Looking or not	−1.4132	0.689	−2.050	0.040	−2.765	−0.062

crossing the intersection first increases by 4.78. Correspondingly, as the vehicle's speed increases, it becomes more likely that the vehicle will pass first through the intersection.

DTA has a positive coefficient, meaning that the road user who is expected to arrive first at the intersection (expectation calculated 15 m from the intersection) is more likely to pass through first. If the cyclist continues pedaling before the decision point, it is 3.12 times more likely that the cyclist will cross the intersection first. The other statistically significant visual parameter is looking at the approaching vehicle before the decision point; if the cyclist is looking at the approaching vehicle, it is 0.25 times more likely that the cyclist will cross the intersection first.

The other variables (gender, wearing helmet, age, bike type, and hand waving) were not found to be statistically significant, so we excluded them from the model. It is worth mentioning that wearing a helmet was significant at $p = 0.095$ in the model: the trend was that those cyclists with no helmet were more likely to pass through the intersection first.

3.4. Validation

The LOOCV result showed an average accuracy of 83 % for the proposed model (with 113 correct and 23 false predictions). Given the fact that the data are naturalistic field data, and the sample size is small, this score is acceptable.

3.5. Inter- and intra-rater reliability results

Table 5 shows the inter- and intra-rater reliability scores, measured through the Cohen's kappa score.

The average Cohen's kappa score for intra-rater reliability is 97 %, and for inter-rater reliability it is 93 %; these values are considered almost perfect agreement.

4. Discussion

- **General model performance**

We found that the kinematic information about interacting road users, along with cyclists' visual cues, were significant predictors of the cyclists' decision to yield to a car at the intersection. The variables that were effective for predicting whether cyclists would yield at the crossing are consistent with those reported in previous studies (Merat et al., 2018; Tafidis et al., 2019; Velasco et al., 2021). Despite much research investigating the effect of implicit communication in pedestrian-vehicle interactions, we found very few studies investigating its effect in predicting cyclists' intent in cyclist-vehicle interactions. Previous studies that attempted to predict cyclist's crossing decision at intersections relied on kinematic information alone; none of them involved cyclists' visual cues in their predictive models (Pucher and Buehler, 2017; Svensson and Pauna, 2010). In this study, two visual parameters (cyclists' pedaling behavior and looking at the approaching vehicle) were found to be effective in predicting whether cyclists intended to cross the intersection ahead of the car.

The presented model in this paper can predict which road user will yield at the intersection when the vehicle still has enough time to react and safely avoid the cyclist (by yielding if the cyclist does not). The outcome of this research can be helpful for automated vehicles to predict cyclist's decision at unsignalized intersections and react safely to the encounters with cyclists. The average vehicle's initial speed in the observed cases was around 12 km/h (3.3 m/s). For this speed, the stopping distance is less than 10 m (Layton and Dixon, 2012). Therefore, the vehicle's active safety systems have enough time from the moment that the cyclist becomes visible (19 m distance to the intersection of trajectories) to intervene or issue a warning to interact safely with the cyclist. For example, in a scenario in the observed intersection with a DTA of 0 and the vehicle traveling at the average speed, the vehicle has 2.1 s to avoid a crash with the bike (if the cyclist decides not to yield) by either intervening or issuing a warning.

So far, threat assessment algorithms have mainly used kinematic information to detect dangerous situations in mixed traffic, ignoring other road users' visual cues. This research shows the importance of implicit communication and behavioral cues in predicting cyclists' intent at crossing scenarios. It should be noted that the effect sizes of the kinematic parameters (vehicle speed, cyclist speed, and DTA) are larger than those of the parameters for cyclist's visual cues. This difference indicates the importance of kinematic information in threat assessment algorithms; acquiring kinematic information from other road users should be the vehicle sensors' priority. However, mounted sensors on the vehicle (like LIDARs and cameras) should provide information about cyclists' visual cues (like head movement and pedaling) to improve threat assessment algorithms even further. Pattern recognition algorithms have been developed to extract cyclists' visual cues like head movement and pedaling from the sensors' raw data (Hagenzieker et al., 2020; Layton and Dixon, 2012). The detection of cyclists' visual cues and the integration of this information will enhance the performance of active safety systems by enabling the threat assessment algorithms to issue a warning or initiate an intervention when the situation is determined to be dangerous. Some cyclists' visual cues, like pedaling, are hard for in-vehicle sensors to detect, but sensors on bikes could provide this information. Therefore, as an alternative to in-vehicle sensing, the cyclist's visual cues, like pedaling, visual scanning, and perhaps even braking, could be transferred to the interacting vehicle wirelessly, informing the other vehicle(s) about the cyclist's intent (Dozza and Gustafsson, 2013).

- **Model predictions**

Our model shows that as the vehicle's speed increases, it becomes

Table 5
Cohen's kappa scores for inter and intra-rater reliability scores.

Variable	Pedaling	Head movement	Gender	Wearing helmet	Age	Severity	Hand gesture	Bike type
Intra-rater reliability scores	96 %	94 %	100 %	100 %	100 %	92 %	100 %	100 %
Inter-rater reliability scores	96 %	87 %	94 %	100 %	100 %	73 %	100 %	100 %

more likely that the vehicle will pass through the intersection first. The reason could be that, based on the information available to them, car drivers think they can clear the intersection sooner in a safe manner. The same tends to be true for cyclists as their speed increases. Since cyclists use physical force to propel the bike, they want to keep their momentum, and the higher their speed, the less willing they are to yield to the motorized vehicle. In total, with the increase in the speed of one road user, the other interacting road users will adapt their behavior, which is an implicit communication from both sides to stay safe (Pucher and Buehler, 2017; Allen et al., 1978; Zernetsch et al., 2020; Dozza and Gustafsson, 2013) The relation of DTA to yielding probability is in line with the expectation that the road user who is expected to arrive sooner at the intersection is more likely to pass through the intersection first (Silvano et al., 2016). Pedaling is a visual cue expressing the cyclist's intention to cross the intersection first, which makes sense because if they want to cross the intersection before the car, they will not stop pedaling. By looking toward the approaching motorized vehicle, the cyclist is implicitly communicating with the driver, demanding the right of way (Grigoropoulos et al., 2022). Visual scanning is a crucial part of dynamic driving, and drivers always search in their peripheral vision to detect possible dangers (Rasanen and Summala, 2000; Grigoropoulos et al., 2022). Cyclists who stop pedaling and look at the approaching vehicle are providing clear signs to any drivers present that they consider yielding at the intersection.

Finally, to determine whether there is an effect of wearing a helmet, we need more observations since this factor was only close to the threshold of being significant. Nevertheless, we could conclude that those cyclists who were not wearing a helmet were more likely to pass through the intersection first; this behavior could be associated with the riskier behavior of cyclists with no helmet (Esmaeilikia et al., 2019).

While we initially sought to investigate the predictive value of cyclists' hand gestures, there were few cases with gestures—which all occurred after the decision point. They were determined to be the cyclist's way of saying thanks to the interacting vehicle for letting them pass through the intersection. As a result, hand gestures were not a factor in predicting cyclists' decisions whether to yield.

We obtained perfect agreement from inter- and intra-rater reliability scores, which shows that the accuracy of annotations from anonymized video was quite good, and they were reasonable to code for a human. The only minor discrepancy between raters happened for the severity level of interactions. The reason for that could be that this parameter is highly subjective (the raters decided the severity level based on their own judgment). Another reason may be that this factor had four categories in contrast to the other variables, that had just two, increasing the possible variability among raters. Nevertheless, we did not include severity levels in the model, so the lower inter-rater reliability scores for this measurement did not affect the model's output.

The model performance suggests that the selected parameters can adequately explain which road user will yield at the intersection, but these are probably not the only parameters indicating the decision to yield. For instance, in the future, researchers should also consider other parameters like mental states (fatigue, cognitive load) and infrastructure design (e.g., visibility condition, angles of intersection, lane width, etc.) in decision making (Bjorklund, 2005; Layton and Dixon, 2012).

- **Post-encroachment-time**

Previous literature shows that interactions with PETs less than 3 s are considered dangerous (Zangenehpour et al., 2016). By this measure, most of the observed interactions in this study were dangerous, but we noticed that the interactions with PETs higher than 3 s could also be dangerous. For example, in scenarios where the drivers approached the intersection at high speed, they had to brake hard to let the bike go, making it dangerous. The PET value for these scenarios is further increased because the vehicle had to increase its speed from zero after stopping and then crossing the conflict zone. Consequently, PET is not a suitable metric to estimate the severity level of interactions between cyclists and motorized vehicles in crossing scenarios when the vehicle stops (or brakes hard) before the intersection. Modifying the PET by involving other variables like deceleration rates, DTA, and road user speeds would increase the accuracy of this safety indicator.

- **Limitations and future work**

Other variables like road user state (fatigue and attention) and infrastructure design could also play a role in the decision making. However, due to the nature of the data in this study, these variables were not captured. It should be noted that the length of the trajectory of interacting road users was limited, especially for the motorized vehicle—because it was unclear when they started to decrease their speed as they approached the intersection. In addition, there was some noise in the speed profiles. Although we tried to filter it out, accelerations extracted from noisy speeds are not reliable, so we did not test variables like the deceleration rates of the road users. As mentioned in the methodology, we only considered interactions between motorized vehicles and cyclists when no other road user was present, in order to avoid other influencing factors and have a clean environment. However, reality can be more complex and multiple interactions may happen at the same time. Collecting data from different locations would add to the generalizability and accuracy of the model, but due to cost and time limitations, we only considered one location. In fact, finding a dataset with detailed information about both interacting road users was a challenge. Further, finding and coding the interaction events manually were time-consuming tasks.

To improve the model performance, the first suggestion is to observe more interaction events and possibly collect data from different locations. The second is to use the deceleration rate of road users as a predictor in the model. More precise and extended sensory data from the interacting road users will provide the chance to observe the yielding phenomenon more in-depth. In addition, other types of computational models could address different aspects of vehicle-cyclist interactions, so it is suggested that future work test other predictive models (like predicting cyclists' trajectory considering the interaction, and survival models for risk assessment in decision making) for this scenario (Dozza and Gustafsson, 2013; Classen et al., 2007).

5. Conclusions

The model proposed in this study shows that road users' kinematic information and cyclists' visual cues are important for predicting the decision to yield. For the first time, the cyclists' visual cues have been proven to help predict yielding at an unsignalized intersection. The LOOCV showed that the model performance is acceptable with the chosen parameters. This model can be used in automated vehicles to predict cyclists' intent in crossing scenarios in order to ensure a safe interaction. Another application of this model could be in threat assessment algorithms for active safety to support FCW and AEB activation when the road users' kinematics do not conform to the model's prediction. However, before it is integrated into commercial safety systems, this model could be improved by observing more interaction events at different locations. Another interesting finding from this study is that interaction events with high PET can also be dangerous; the measure is not capable of determining the severity level of the interaction between a vehicle and a cyclist at a crossing scenario due to the possibility that one of the vehicles stops. Hence, a robust safety metric that could involve road user's speed and acceleration is needed for these scenarios.

Finally, the proposed model in this study shows that implicit communication and cyclists' behavioral cues are important for predicting cyclists' behavior in crossing scenarios. Therefore, AVs should consider not only the kinematics of other road users but also their behavior, in order to make more accurate predictions and improve their safe operation.

CRediT authorship contribution statement

Ali Mohammadi: Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Giulio Bianchi Piccinini:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Marco Dozza:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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.

Data availability

The authors do not have permission to share data.

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