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Cyclists' interactions with professional and non-professional drivers: Observations and game theoretic models☆

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ABSTRACT

According to crash data reports, most collisions between cyclists and motorized vehicles occur at unsignalized intersections (where no traffic lights regulate vehicle priority). In the era of automated driving, it is imperative for automated vehicles to ensure the safety of cyclists, especially at these intersections. In other words, to safely interact with cyclists, automated vehicles need models that can describe how cyclists cross and yield at intersections. So far, only a few studies have modeled the interaction between cyclists and motorized vehicles at intersections, and none of them have explored the variations in interaction outcomes based on the type of drivers involved. In this study, we compare non-professional drivers (represented by passenger car drivers) and professional drivers (truck and taxi drivers). We also introduce a novel application of game theory by comparing logit and game theoretic models' analyses of the interactions between cyclists and motorized vehicles, leveraging naturalistic data. Interaction events were extracted from a trajectory dataset, and cyclists' non-kinematic cues were extracted from videos and incorporated into the interaction events' data. The modeling outputs showed that professional drivers are less likely to yield to cyclists than non-professional drivers. Furthermore, the behavioral game theoretic models outperformed the logit models in predicting cyclists' crossing decisions.

1. Introduction

Cycling as an active mode of transportation is on the rise in European countries (Pucher and Buehler, 2017). The increasing prevalence of cycling in urban areas underscores the growing importance of ensuring the safety of cyclists (Cantisani et al., 2019). Recent European crash data indicate an increasing proportion of fatalities among cyclists, in contrast to the declining trend observed for drivers of motorized vehicles (hereafter referred to simply as 'vehicles'). Intersections, particularly unsignalized ones, emerge as primary sites for conflicts between bicycles and motorized vehicles (Bjorklund, 2005). Notably, Isaksson-Hellman and Werneke's research has revealed that over 70 % of bicycle crashes occur in areas where cyclists share pathways with motorized vehicles (Isaksson-Hellman and Werneke, 2017). Unsignalized intersections, which operate on priority rules, require effective communication and

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agreement between cyclists and drivers (Isaksson-Hellman and Werneke, 2017). By law, drivers at these intersections commonly yield to cyclists, allowing them to proceed first (Bjorklund, 2005). However, research by Svensson et al. has shown that, in 42 % of cases in Sweden, drivers deviated from this norm and did not give priority to cyclists (Svensson, 2010). Comprehensive understanding and modeling of how cyclists and drivers engage with each other and convey intent in these scenarios are essential in order to incorporate their dynamics into the operational framework of automated vehicles (AVs) and safety systems.

1.1. Cyclist-vehicle interaction models

As noted by Hagenzieker et al., several studies have examined and modeled the interaction between motorized vehicles and bicycles at crossing scenarios, with recent investigations focusing specifically on unsignalized intersections (Hagenzieker, 2020). Silvano et al. (2016) constructed a logit model employing kinematic information, such as speed and distance, to anticipate cyclists' yielding behavior. Their findings revealed that the cyclist's decision to yield was significantly influenced by the cyclist's time to arrival at the intersection and the vehicle's speed (Silvano et al., 2016). It is worth noting that their study took place at a roundabout rather than an unsignalized intersection, and a complete trajectory dataset was not utilized; instead, only the presence of the bicycle and the car at discrete locations at the intersection was considered. In a different approach, Bella & Silvestri (2018) utilized a driving simulator to analyze the impact of various infrastructure designs on the driver's response process. Specifically, they examined the effectiveness of safety countermeasures such as pavement color and raised islands at reducing drivers' speed when interacting with a cyclist at a crossing (Bella and Silvestri, 2018). Velasco et al. (2021) employed a virtual reality (VR) headset to present participants with videos depicting oncoming vehicles as they cycled toward an unsignalized intersection. Participants had to decide whether to cross or yield, and the factors influencing their decision were observed. The primary factors affecting the cyclist's decision to cross ahead of the vehicle were the distance to the vehicle and whether the cyclist had the right of way (Velasco et al., 2021). In a recent study, Mohammadi et al. examined the interaction between cyclists and motorized vehicles by analyzing naturalistic data obtained from a real intersection. Their findings indicate that kinematic factors such as the difference in the time to arrival at the intersection, the speed of both road users, and the cyclists' non-kinematic cues including head turn and pedaling could be utilized to predict who will cross the intersection first (Mohammadi et al., 2023; 2024). Other researchers have also highlighted the importance of utilizing cyclists' non-kinematic cues, such as whether cyclists look towards the oncoming vehicle, to predict their intentions in complex scenarios (Golman et al., 2020; Grigoropoulos et al., 2022). In a 2014 study, Hemeren et al. presented participants with videos of cyclists either proceeding straight or turning left at an intersection, in order to investigate the relevance of key non-kinematic cues for predicting the cyclists' future paths. Their research identified speed, head turn, and body position (leaning or sitting upright) as crucial indicators of the cyclists' intentions (Hemeren et al., 2014).

By modeling cyclists' interactions with vehicles, developers can improve AV systems' predictive capabilities. As the systems become better equipped to handle diverse traffic scenarios, they will not only improve the safety of cyclists but also increase public acceptance and trust in AV technology. Ultimately, understanding and accurately modeling cyclists' behavior is essential for designing AVs that can seamlessly integrate into the existing transportation ecosystem, ensuring the safety and efficiency of future mobility solutions.

1.2. Game theory

Game theory is a methodology for modeling that offers valuable insights into human decision-making processes. This modeling approach expands the principles of optimal control theory to address decentralized multi-agent decision problems (Camara and Fox, 2021). It elucidates the dynamics of interactions involving multiple agents with different interests; each agent's decisions are typically influenced by the actions of the others (Li et al., 2023). In conventional game theory, agents continuously adjust their decisions and beliefs until a state of mutual satisfaction is reached, known as the Nash equilibrium. Nash equilibrium is the fundamental concept of game theory, which assumes that players are perfectly rational—self-interested and inclined to make optimal choices.

Game theoretic approaches have proven to be powerful tools for modeling interactions between road users, mainly between pedestrians and vehicles (Hemeren et al., 2014; Camara and Fox, 2021; Li et al., 2023). However, some studies have found that road user interactions do not always arrive at a Nash equilibrium. Behavioral game theory (BGT), on the other hand, includes insights from psychology and behavioral economics (Camerer & Ho, 2015; Wu, Chen, Jia, Li, & Liang, 2019). Unlike conventional game theory, which assumes perfectly rational and utility-maximizing players, BGT recognizes that people may not always behave in a strictly rational manner (Kalantari, 2023). It considers realistic psychological elements such as emotions, cognitive biases, and social preferences in analyzing strategic interactions (Öz et al., 2010). Kalantari et al. (2023) showed that BGT surpasses conventional game theory in predicting pedestrians' decision-making during interactions with a vehicle (Kalantari et al., 2023).

To date, the applicability of the BGT modeling approach has not been examined in the context of cyclist-vehicle interactions. Moreover, there have been no comparative analyses of BGT and logit models' simulations of these interactions.

1.3. Professional versus non-professional drivers

This study also delves into the critical factor of driver type (professional or non-professional). A growing body of research has highlighted differences in how they perform driving tasks in terms of risk perception, which could significantly influence the dynamics of encounters with cyclists. A study by Bahar et al. (2010) concluded that taxi drivers, minibus drivers, and heavy vehicle drivers are more likely to engage in risky driving behaviors than non-professional drivers (Öz et al., 2010). The findings revealed differences in stress reactions, speeding, number of penalties incurred, and frequency of accident involvement between the different groups. Regression analyses showed that aggression, dislike of driving, and hazard monitoring were related to accident involvement, while dislike of driving and thrill-seeking were related to speeding on city roads. Moreover, professional drivers self-reported greater stress and more risky driving behaviors than non-professional drivers.

Wang et al. (2014) examined the correlations between self-reported behaviors, attitudes about driving violations, and perceived countermeasures among 2,437 professional drivers involved in accidents in China (Wang et al., 2014). The authors investigated the connection between attitudes, behaviors, and additional characteristics of the drivers. Their results showed differences between male and female drivers: males were more prone to violations, errors, and lapses. Taxi drivers exhibited higher risky driving tendencies than other professional drivers. In another study, Nordfjærn et al. (2012) examined variations in psychological safety factors between professional and non-professional drivers (Nordfjrn et al., 2012). They used questionnaire responses from 6,203 Norwegian drivers to investigate attitudes towards traffic safety, driver behavior, safety priorities, and anxiety regarding road traffic accidents. Using descriptive statistics, they investigated how the two groups of drivers perceive safety aspects of driving. Professional drivers were found to use seat belts less often, exhibit less cautious driving, and report higher accident probabilities. However, they had safer attitudes towards drunk driving. The study highlighted the need for targeted safety campaigns which consider the challenges and attitudes specific to the professional driver population (Nordfjrn et al., 2012).

Wu et al. (2016) investigated the differences in risky behaviors at signalized intersections between taxi drivers and non-professional drivers (Wu et al., 2016). Using a driving simulator, they tested 49 participants (23 taxi drivers and 26 non-professional drivers) in a red-light-running scenario at a signalized intersection. Despite having lower operating speeds, the taxi drivers exhibited a higher rate of red-light running, possibly due to economic pressures leading them to cross intersections during the yellow signal. However, taxi drivers showed better crash avoidance performance by deviating from the lane in order to steer clear of the obstacle, while the non-professional drivers tended to rely on abrupt deceleration, which was a less successful reaction. The study suggests that to improve overall road safety within the taxi transport industry, the following are needed: enhanced traffic safety awareness among taxi drivers, implementation of a penalty system, stricter regulations, and rigorous training for new taxi drivers.

While existing studies have explored general driving behaviors and risk perceptions among professional drivers, the nuances of their interactions with vulnerable road users (VRUs: e.g., pedestrians and cyclists) are still largely unknown. There remains a notable gap in the research comparing how professional and non-professional drivers interact with VRUs, such as cyclists and pedestrians.

The primary goal of this study is to provide insights into the interactions between bicycles and motorized vehicles at unsignalized intersections. The research objectives are as follows: 1) to model which agent goes first during interactions between cyclists and vehicles at unsignalized intersections using two different modeling approaches, 2) to explore the differences in the interactions between vehicles and cyclists based on driver type (professional vs. non-professional), and 3) to quantify the effectiveness of two modeling types (logit model and BGT) in predicting cyclists' yielding decisions. To achieve these objectives, naturalistic data from an unsignalized intersection in Sweden were utilized. Two hypotheses, one methodological and one behavioral, underpin the objectives. The first methodological hypothesis was that due to the nature of human interactions, BGT would outperform the logit model (Kalantari et al., 2023). The second behavioral hypothesis was that because time is so important for professional drivers, they would yield less often than non-professional drivers (Nordfjrn et al., 2012).

This paper is structured as follows: The methodology section outlines the study's design and implementation, including information on participants, tools, and data analysis. Subsequent sections present and discuss the results, shedding light on cyclists' responses

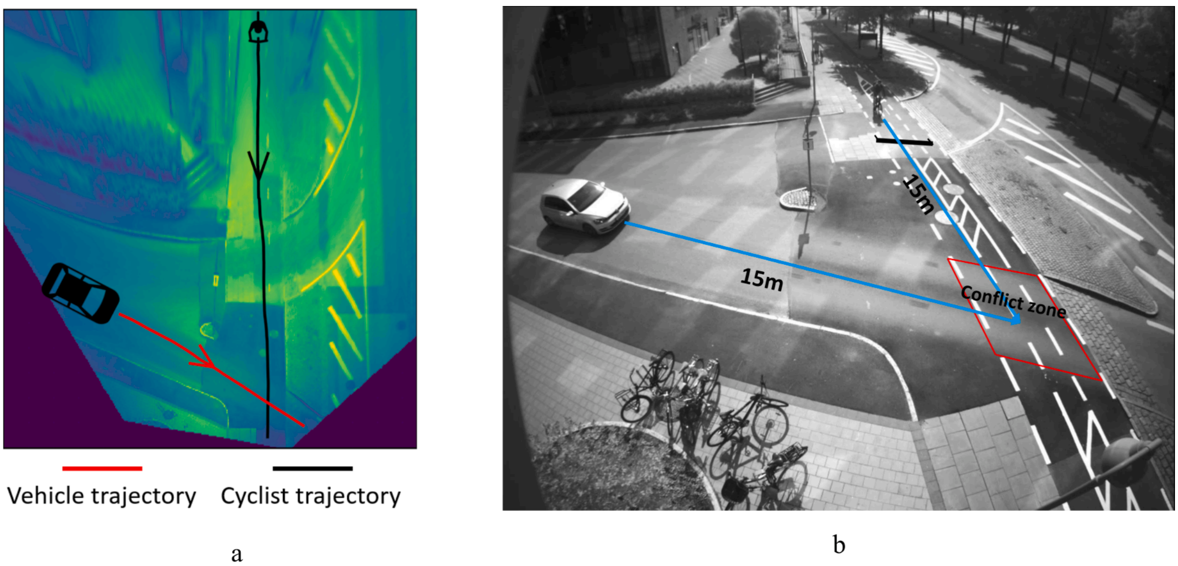


Fig. 1. (a) The layout of the intersection along with the trajectories taken by the vehicle and the bike, (b) a view of the intersection from the Viscando sensor, depicting the conflict zone (used to identify the factors influencing the decision of the car driver to yield).

during interactions with approaching vehicles at intersections. The conclusion summarizes the key findings, discusses their implications, and suggests potential avenues for future research.

2. Methodology

2.1. Data collection

The data for our study were gathered at an unsignalized urban intersection in Gothenburg, Sweden, with the following GPS coordinates: 57°42′31.1″N, 11°56′22.9″E. According to Swedish traffic regulations, motorized vehicles are required to yield to cyclists at unsignalized intersections. Cyclists, in turn, are advised to be attentive to surrounding vehicles and cross the intersection cautiously.

The study utilized stereovision and an AI-based sensor provided by Viscando (VISCANDO), mounted at the intersection's corner, to record the trajectories of all road users over a 14-day period in June 2019. Data collection occurred from 6:00 to 18:00 each day. Road user categories included pedestrians, cyclists, motorized vehicles, and heavy vehicles, with trajectory data (positions, speeds, and headings) recorded at a frequency of 20 Hz.

The analysis presented in this paper focused on interaction events involving a single vehicle and a single bicycle approaching the intersection; instances involving other road users were excluded. In traffic, the interaction among road users sharing the same infrastructure can be defined as a cyclic process involving perception, planning, and action. This interaction, based on predictions, aims to ensure safety and comfort while meeting mobility needs, and also serves to communicate and understand intentions (Thalya et al., 2020). The video clips were observed to determine if there was any communication of intent or negotiation between the cyclist and the driver.

The average lengths of the trajectories for bicycles and vehicles were approximately 23 m and 16 m, respectively, working backwards from their convergence point in the middle of the intersection to the start of the intersection. Fig. 1.a shows the cyclist and vehicle trajectories leading up to the interaction.

2.2. Interaction events

The process of identifying and selecting interaction events (in which a cyclist and a vehicle approach the intersection closely in time) was based on the difference in time to arrival (DTA) at the intersection. To determine interaction events, we established equal distances of 15 m to the convergence point along both the cyclist's and vehicle's trajectories, starting from where the cyclist enters the intersection. The DTA indicates which road user arrived first at the 15-meter distance from the intersection (Fig. 1b). A positive DTA indicates the car arrived first, while a negative DTA indicates the bicycle arrived first. Fig. 1b illustrates the observed intersection and the distances used to calculate DTA from the camera's perspective.

We set a DTA threshold of ± 7 s based on a preliminary visual assessment of the video events. An algorithm was developed and implemented to identify interaction events in the trajectory dataset below this threshold, and corresponding videos were manually verified. Kinematic information for the involved road users was extracted from the trajectory dataset, and the corresponding videos were annotated to capture additional information.

A total of 156 confirmed interaction events between motorized vehicles and cyclists were identified in the dataset. Table 1 lists the 15 variables defined and coded for each interaction event. Table 1 contains variables extracted from the trajectory dataset, and variables obtained from video annotation.

Kinematic information consists of the speeds of the involved road users. Additionally, to understand the cyclists' behavior, three variables indicating implicit communication were coded as time series: pedaling activity, looking toward the approaching vehicle, and hand gestures (e.g., signaling the vehicle to cross first or expressing gratitude). These variables were coded for each timestamp throughout the entire trajectory of each cyclist (Table 1).

For each interaction event, post-encroachment time (PET) and projected PET were calculated, and DTA was recorded (Allen et al.,

Table 1
Variables coded for each interaction event.

	Variable	Unit	Data type	Description
1	Cyclist speed	m/s	time series	cyclist speed (from the trajectory dataset)
2	Vehicle speed	m/s	time series	vehicle speed (from the trajectory dataset)
3	Cyclist pedaling	dummy	time series	0 for the time stamps when the cyclist is not pedaling and 1 otherwise
4	Cyclist's head movement	dummy	time series	0 for the timestamps when the cyclist is looking-ahead and 1 otherwise
5	Cyclist's hand waving	dummy	time series	0 for timestamps no hand gesture by the cyclist and 1 otherwise
6	PET	sec	numeric	post-encroachment time
7	Projected PET	sec	numeric	projected post-encroachment time
8	DTA	sec	numeric	difference in time to arrival at the beginning of the intersection
9	Crossing decision	dummy	categorical	1 when cyclists pass first, and 0 when vehicles pass first
10	Cyclist's gender	dummy	categorical	0 for male, 1 for female
11	Age	categorical	categorical	0 for adult, 1 for child, 2 for elder
13	Wearing helmet	dummy	categorical	0 for wearing helmet, 1 for not wearing helmet
14	Bike type	dummy	categorical	0 for normal bike, 1 for e-bike
15	Vehicle type	categorical	categorical	0 for passenger cars, 1 for truck, 2 for taxi

Table 2
Payoff parameters of the game-theoretic models.

Parameter	Description	Unit
$r = \frac{1}{\Delta TTA}$	Risk perception for cyclists/drivers.	1/s
e	A multiplier applied to the negative utility of delay to offset the additional waiting time incurred when both agents opt to pass simultaneously, necessitating the need to prevent collisions, such as through sudden braking.	–
β	Coefficient: ΔTTA coefficient enabling adaptable model performance across various scenarios.	1/s
E_c	A multiplier representing cyclist's elevated risk perception when they realize that drivers do not intend to yield to them (takes value 1 when the driver is professional and 0 otherwise).	
E_d	A multiplier representing the driver's elevated risk perception when they notice that the cyclist intends to let them pass first (takes value 0 when the driver is professional and 1 otherwise).	
n	A multiplier that helps the model distinguish between the driver types (passenger cars versus taxis and trucks) and is relative to the risk perception of the road user (≥ 1).	
m	A multiplier that discourages both agents from waiting when each thinks that the other one will yield at the interaction point (≥ 1).	–

1978). The PET is defined as the time interval between the moment one road user (such as a vehicle, cyclist, or pedestrian) vacates a space at an intersection and the moment another road user enters the same space. A shorter PET indicates a higher potential for collision, as it reflects a smaller temporal gap (Allen et al., 1978). The projected PET is an estimate of the time it will take for the second road user to reach the conflict zone after the first road user has crossed it. In other words, projected PET is calculated at the point in time when the first road user leaves the conflict zone, by dividing the second road user's distance left to the conflict zone by its speed at that point in time. The interaction outcome was coded as binary: 0 if the cyclist crossed the intersection first and 1 if the car crossed first. Cyclist age was grouped into three categories: elderly, adults, and children. Additional variables included whether cyclists wore helmets and the type of bike (e-bike or normal bike). Vehicle type was divided into three categories: passenger cars, trucks, and taxis. Taxis and truck drivers are considered professional drivers, while those driving passenger cars are considered non-professional.

2.3. Decision point

An analysis of cyclists' speed profiles revealed that cyclists typically began to either accelerate or brake approximately eight meters before reaching the intersection point. Consequently, we identified this distance as the decision point for cyclists and assessed the occurrence of non-kinematic cues (such as pedaling, looking towards the vehicle, and hand waving) before this point.

One of the modeling objectives is to use these cues to predict cyclists' crossing decisions before the cyclist reaches the decision point. Cyclists' non-kinematic cues were recorded during the four meters traveled before the decision point as dummy variables.

Speed data for both the cyclist and the vehicle were extracted when they entered the field of view of the trajectory-tracking sensor (19 and 15 m from the intersection point for the bike and vehicle, respectively). The speeds were recorded at the onset of the interaction once they entered the field of view, since the initial perception of the other's speed would influence each road user's subsequent behavior.

2.4. Inter- and intra-rater reliability for annotations

Two analysts annotated the videos for the selected interactions. We evaluated both inter-rater reliability, which determines agreement among different analysts coding the videos, and intra-rater reliability, which measures the consistency of annotations when a single analyst repeats the process. Existing research suggests that recoding 10–25 % of the data is a typical percentage when there is good inter-rater reliability (O'Connor and Joffe, 2020). In this study, we recoded 25 % of the interaction events.

In addition, Cohen's kappa method served as an indicator of the level of agreement for both intra- and inter-rater reliability measures (O'Connor and Joffe, 2020). The scale of this indicator ranges from 0 to 1, where 0 signifies no agreement, and 1 indicates perfect agreement between raters. A value within the range of 0.81–1 is considered almost perfect agreement between raters. The formula for calculating Cohen's kappa is:

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

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 crosses the intersection first given the defined parameters, we used two modeling approaches: logistic regression and the game theoretic approach. The logit model was first utilized for inferential testing to identify the variables that significantly influence the outcomes of cyclist-vehicle interactions. A comparative analysis was then performed between logit models of varying complexity and behavioral game theory (BGT) models to determine which more successfully captured the dynamics of these interactions.

2.5.1. Logit model

Logistic regression is a statistical approach that represents the likelihood of an event occurring, through a linear combination of one or more independent variables, with the log-odds serving as the basis. When applied in regression analysis, this approach requires the estimation of the logit model's parameters, specifically the coefficients within the linear combination (Thalya et al., 2020). The logit model was used in this study to model the interaction outcome, given the defined parameters. The general form of a logit model can be expressed as:

$$P = \frac{e^{(a+\Sigma_i b_i x_i)}}{1+e^{(a+\Sigma_i b_i x_i)}} \tag{2}$$

where,
P = the probability that a case is in one category.
b_i = vector of parameters to be estimated.
x_i = independent variables.
a = intercept.

2.5.2. Game theoretic model

A two-agent game-theoretic model based on the agents' risk perception and efficiency in interactions was developed. The new model was adapted from studies primarily focused on modeling driver-pedestrian interactions, so its payoff matrix was modified to reflect the differences between pedestrians and cyclists (Camerer, 2003; Hemeren et al., 2014). Further, the original model did not distinguish between professional and non-professional drivers. Additionally, in this study, both agents (driver and cyclist) continuously move towards the intersection, whereas in vehicle–pedestrian interaction scenarios, pedestrians usually stop before entering the crossing to evaluate the situation. The estimated TTA (Time to Arrival) for cyclists and vehicles is the predicted duration until they reach the intersection point of their paths, starting from the moment the interaction begins. Thus, the difference in TTAs (ΔTTA) matters the most here, unlike vehicle–pedestrian interactions at crossings.

Similar to the logit model, we considered two versions of the model—one incorporating the potential influence of driver type on interactions and the other excluding this variable as a predictor. Tables 2 and 3 present the payoff parameters and formulations, respectively, of both versions. The formulation in Table 3 was derived from the following conditions:

1. When both agents start to cross without yielding, they receive negative scores for risk perception and lose time—equal to a coefficient (β) and ΔTTA multiplied by a factor (e)—for the emergency braking ultimately required to avoid a collision.
2. When professional drivers aim to pass first, their risk perception could be mitigated if they notice the cyclist is letting them pass. Conversely, cyclists may experience higher risk when attempting to pass first if they believe that professional drivers would not yield to them. In this context, E_d and E_c represent the excessive risk perceptions of the driver and the cyclist, respectively. E_d is 0 and E_c is 1 when the driver is a professional, and vice versa otherwise.
3. The yielding agent always loses βΔTTA, except for the situation where both of them do not intend to pass immediately; in this instance, both will lose βΔTTA with a multiplier (m)— which is a multiplier designed to discourage both agents from waiting by increasing the penalty in that scenario.

The dual accumulator paradigm, a BGT model, was employed as the game solution. In this model, agents formulate preferences by accumulating evidence for the value of both their own and the other agent's available actions. This accumulation is based on reciprocal beliefs about the action the other agent will take, which in turn is based on accumulated values, making the two accumulation processes coupled. The process involves a finite number of accumulation steps in payoffs, drawing inspiration from established cognitive models of preferential choice (Golman et al., 2020). This model has outperformed conventional game-theoretic models in the context of vehicle–pedestrian interactions, but it has never been tested for vehicle-cyclist interactions (Kalantari et al., 2023).

The following equations show the model formulation:

$$\widehat{V_{D,a}}(t) = \gamma \widehat{V_{D,a}}(t-1) + \omega \sum_{a'} P_{C,a'}(t-1) v_{D,a,a'} \tag{3}$$

$$\widehat{V_{C,a}}(t) = \gamma \widehat{V_{C,a}}(t-1) + \omega \sum_{a'} P_{D,a'}(t-1) v_{C,a,a'} \tag{4}$$

Table 3
Payoff formulation.

	Cyclist pass	Cyclist yield
Vehicle pass	$-r-\beta e\Delta TTA,\ -r(nE_c+E_d)-\beta e\Delta TTA$	$r(nE_c+E_d)+\beta\Delta TTA,\ -\beta\Delta TTA$
Vehicle yield	$-\beta\Delta TTA,\ r+\beta\Delta TTA$	$-m\beta\Delta TTA,\ -m\beta\Delta TTA$

$$P_{\mathrm{D},a}(t) = \frac{e^{\lambda \widehat{V_{D,a}}(t)}}{\sum_{\mathrm{a}} e^{\lambda \widehat{V_{D,a}}(t)}} \tag{5}$$

$$P_{\mathrm{C},a}(t) = \frac{e^{\lambda \widehat{V_{C,a}}(t)}}{\sum_{a} e^{\lambda \widehat{V_{C,a}}(t)}} \tag{6}$$

where $\widehat{V_{\mathrm{D},a}}(t)$ and $\widehat{V_{\mathrm{C},a}}(t)$ are the accumulated values of taking action $a \in \{cross, yield\}$, for driver and cyclist, respectively; $P_{\mathrm{D},a}(t)$ and $P_{\mathrm{C},a}(t)$ are the currently estimated probabilities (i.e., probability-weighted averages) that the driver and cyclist (respectively) will take action a; and $v_{\mathrm{D},a,a'}$ and $v_{\mathrm{C},a,a'}$ are the payoffs to the driver and cyclist (respectively) if each takes action a and the other takes action a'. The weighting factor ω determines the influence of an agent's belief about the other agent's actions on their own value accumulation. The sensitivity parameter λ controls the responsiveness of the agent to accumulated values, affecting the probability of selecting a particular action. Lastly, the discount factor γ represents the agent's memory of past values, influencing how much previous accumulations impact current decisions. These parameters collectively help to model the reciprocal and dynamic decision-making process in vehicle-cyclist interactions. As λ increases, agents are more inclined to select the option with the highest value, whereas lower values of this parameter indicate that agents exhibit a higher degree of randomness in their decision-making. In addition, the parameters ω and γ in Eqs. (3) and (4) define the rate of change during an update of the agents' activations (preferences) and beliefs.

2.6. Model fit

All the models were fitted to the experiment dataset using the maximum likelihood estimation method, computing likelihood and log-likelihood functions as follows:

$$LL(\theta) = \sum_{i=1}^{n} logL_i$$

where n is the number of events and p is the model-predicted probability of the cyclist i passing first; X_i specifies the scenario condition on each event, given model parameters θ. θ encompasses b_0 (intercept) and b_1 to b_5 for the logit models, depending on their variants and the set of predictors. For the BGT model with ΔTTA as its predictor, θ consists of β, e, and m; for the one with ΔTTA and driver type as its predictors, θ consists of β, e, m and n (see the next section).

All the models were simultaneously fitted to datasets for both driver types, with shared parameters. The logit model used for inferential testing was fitted using Statsmodels. To ensure fair comparisons, all the compared models—both logit models of varying complexity and the BGT models—were fitted using the same method (Powell's method), implemented in *Scipy* (Kalantari et al., 2023). To compare different model fits and performance, the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the error indicator Root Mean Squared Error (RMSE), were used:

AIC evaluates model quality by balancing goodness-of-fit (log-likelihood) and model complexity (number of parameters). It penalizes models with too many parameters to avoid overfitting:

$$\mathrm{AIC} = 2k + 2\mathrm{NLL} \tag{9}$$

where k is the model's number of free parameters, and NLL is the negative log-likelihood of the model measuring the likelihood of the observed data given the model's predictions. Lower NLL indicates a better model fit of the model.

BIC is similar to AIC but includes a stronger penalty for models with more parameters. Lower BIC values, similar to AIC, indicate better model fit while accounting for sample size and complexity:

$$\mathrm{BIC} = k\ln(n) + 2\mathrm{NLL} \tag{10}$$

where n is number of events (sample size).

RMSE measures the average magnitude of the error between observed and predicted probabilities. It provides an idea of how well the model predicts the observed outcomes.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \widehat{y_i})^2}$$

where y_i is the observed outcome for event i and $\widehat{y_i}$ is predicted probability for event i.

Table 4
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	3.99	3.64	1.88	2.7	4.05
STD	0.94	1.03	2.15	1.03	2.49
Min	1.99	0.26	−2.92	0.89	0.68
Max	7.58	6.11	8.58	5.87	8.36

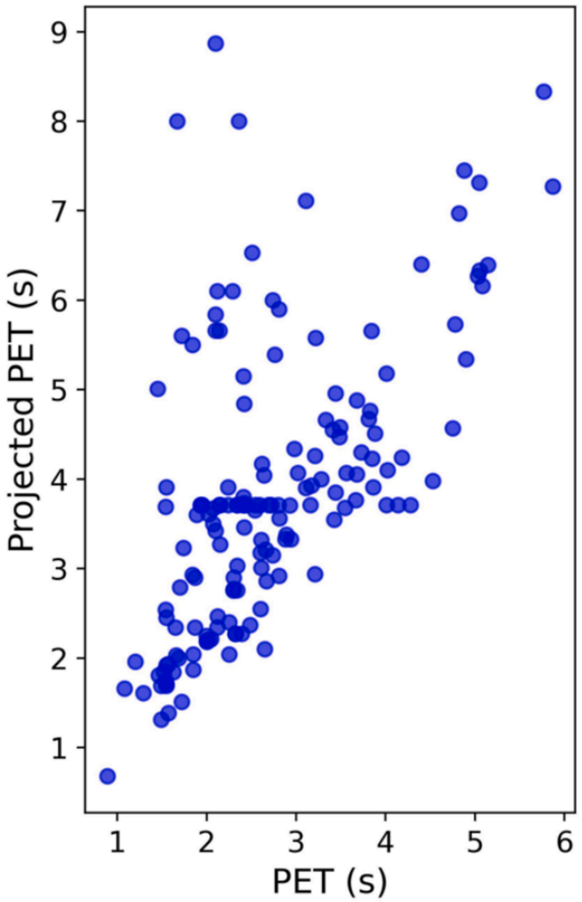
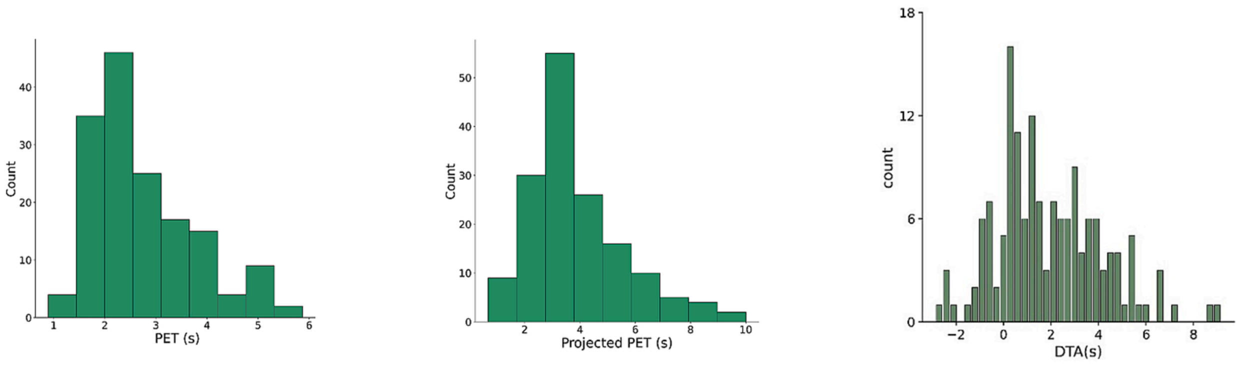


Fig. 2. Scatter plot of PET values against respective projected PET values.



a b c

Fig. 3. Distributions of (a) PET, (b) projected PET, and (c) DTA.

3. Results

3.1. Data description

We extracted 156 interaction events between cyclists and motorized vehicles. Among the cyclists, 38 % were women and 62 % were men. In 70 % of the cases, the cyclist wore a helmet. Only two cyclists were riding e-bikes, and there were nine elderly people among the cyclists. On no occasion were cyclists waving their hands at the driver. In 61 % of the events, the cyclist passed through the

Table 5
Factors tested in the models.

	Variable	Unit	Type	Description
1	DTA	sec	numeric	difference in time to arrival to the intersection between the road users
2	Cyclist speed	m/s	numeric	cyclist's speed at interaction onset
3	Vehicle speed	m/s	numeric	vehicle's speed at interaction onset
4	Gender	–	categorical	0 for male, 1 for female,
5	Age	–	categorical	0 for adult, 1 child, 2 elder
6	Wearing a helmet	–	categorical	0 wearing helmet, 1 not wearing helmet
7	Looking towards the vehicle	–	categorical	1 looking to the vehicle before the decision point, 0 otherwise
8	Pedaling	–	categorical	1 pedaling and 0 not pedaling before the decision point
9	Driver type	–	categorical	0 passenger cars, 1 for truck and taxi
10	Cyclist distance	m	numeric	distance of the bike to the intersecting point at interaction onset
11	Vehicle distance	m	numeric	distance of the vehicle to the intersecting point at interaction onset
12	Cyclist TTA	s	numeric	TTA of the bike to the intersecting point at interaction onset.
13	Vehicle TTA	s	numeric	TTA of the vehicle to the intersecting point at interaction onset.
14	ΔTTA	s	numeric	$TTA_{\mathrm{Vehicle}} - TTA_{\mathrm{cyclist}}$

intersection first. In 72 % of the events, the cyclists interacted with non-professional drivers; the remaining 28 % involved professional drivers (10 % in trucks, and 18 % in taxis). Summary statistics of the interaction events are shown in Table 4.

Fig. 2 presents a scatter plot of PET values against their corresponding projected PET values. Projected PETs are longer on average because they were waiting for the first road user to cross the conflict zone, so their speed was quite low when the first road user left the conflict zone. Fig. 3a–c depicts the distributions of PET, projected PET, and DTA. As shown in Table 4 and the PET distribution in Fig. 3a, the average PET was 2.7 s.

Most DTA values are positive, indicating that in most interactions the vehicle entered the intersection first (i.e., reached a distance less than 15 m from the intersection point before the cyclist did). When cyclists entered the intersection first, they usually passed through without being perceptibly influenced by the vehicle.

Table 5 outlines the variables tested in the models. Some variables in Table 1, like PET and projected PET, were obtained after the interaction; since they cannot predict the outcome decision, they are not included in the models. The TTAs and distances in Table 5 were calculated by post-processing the data. The estimated TTA for cyclists and vehicles is the predicted time until they reach the point where their paths intersect, measured from the moment the interaction begins. ΔTTA is the difference in the estimated Time to Arrival (TTA) between the two interacting road users, indicating which one will reach the convergence point of trajectories first and by how much.

Table 6 displays the inter- and intra-rater reliability scores, assessed using Cohen's kappa score. The average Cohen's kappa scores indicate almost perfect agreement: 0.97 for intra-rater reliability and 0.93 for inter-rater reliability. These results indicate that the annotations from the anonymized videos are reliably accurate, despite being based on subjective coding.

3.2. Modeling outputs

Table 7 presents the estimation results concerning the interaction outcome for variables that exhibited statistical significance in the logit model. Other variables in Table 5, including cyclist speed and vehicle speed, were omitted from the model because they are collinear to variables like TTAs. The variables significantly influencing the decision to yield are the cyclist distance, cyclist TTA, vehicle TTA, driver type, pedaling, and whether the cyclist is looking towards the vehicle.

3.2.1. Inferential testing

The variables Gender and Wearing a helmet were not found to be statistically significant (Table 7). Pedaling had a positive association (with a coefficient of 1.292), indicating that the act of pedaling is linked to an increase of 1.292 in the log-odds that the cyclist will cross first. Similarly, looking towards the vehicle was associated with a substantial increase of 1.397 in the log-odds that the cyclist will cross first. In contrast, cyclist distance showed a negative association (with a coefficient of −0.505), implying that an increase in cyclist distance is correlated with a notable decrease of 0.505 in the log-odds that the cyclist will cross first.

Furthermore, the variables cyclist TTA (Time to Arrival) and vehicle TTA (Time to Arrival) demonstrated negative and positive associations (coefficients of −0.66 and 1.16, respectively). The negative coefficient signifies that a greater cyclist TTA is associated with a decrease of 0.664 in the log-odds of the cyclist crossing first, while a larger vehicle TTA corresponds to a substantial increase of 1.164 in the log-odds of the cyclist crossing first. Additionally, driver type revealed a negative association: there is a significant decrease of 0.783 in the log-odds of the cyclist crossing first when the vehicle is driven by a professional driver.

Table 6
Cohen's kappa scores for inter and intra-rater reliability scores.

Variable	Pedaling	Head movement	Gender	Wearing helmet	Age	Hand gesture	Bike type
Intra-rater reliability scores	0.96	0.94	1	1	1	1	1
Inter-rater reliability scores	0.96	0.87	0.94	1	1	1	1

Table 7
Results of interaction outcomes using the logit model (1 = cyclist crossed first, 0 = cyclist yielded).

	Estimate	Std. Error	z value	Pr(>|z|)	95 % CI L	95 % CI U
(Intercept)	5.3	1.49	3.56	0.00	2.39	8.23
Gender	−0.18	0.54	−0.34	0.73	−1.24	0.87
Wearing helmet	−1.08	0.52	−2.06	0.08	−2.11	−0.05
Pedaling	1.29	0.53	2.45	**0.01**	0.26	2.32
Looking towards the vehicle	1.39	0.59	2.38	**0.01**	0.25	2.55
Cyclist distance	−0.5	0.14	−3.70	**0.000**	−0.77	−0.24
Cyclist TTA	−0.66	0.23	−2.84	**0.004**	−1.12	−0.21
Vehicle TTA	1.16	0.26	4.46	**0.000**	0.65	1.68
Driver Type	−0.78	0.31	−2.54	**0.011**	−1.39	−0.18
	logLik	R-squ.	df.resid	Observations		
	−65.91	0.146	147	156		

3.3. Model comparison

In the subsequent section, the outputs of the two modeling approaches (logit and BGT) are compared; the results are presented in Table 8. Three logit models (I, II, and III) and two BGT models (I and II) were developed. Both Model Is used ΔTTA as their predictor, and both Model IIs used a combination of ΔTTA and driver type as their predictors. The logit model's third variant, Model III, incorporated all six significant variables from Table 7 as predictors.

Since the TTAs of both agents were found to be significant and both agents were moving towards the intersection, we utilized ΔTTA to estimate their difference in arrival at the intersection point (instead of individual TTAs and distances). As delineated by the performance metrics AIC and BIC, the accuracy of both models improved when the driver type parameter was included (Table 8). This improvement was more prominent for the BGT models, which BGT model II outperformed all logit models, even those with six free parameters (Model III) in terms of both accuracy and model parsimony.

Fig. 4 illustrates the probability of cyclists crossing first across various ΔTTA values for all models. Here, Model I refers to the baseline models for both the logit and BGT models, while Model II refers to both the logit and BGT models accounting for the effect of driver type. From the figure, together with the results of Table 8, it can be seen that the BGT model excels in capturing observations over different ΔTTA values. While incorporating the driver type variable in Model II enhanced the overall performance for both the logit and BGT models, this improvement is particularly evident in the BGT models, where the plots of predicted behavior are much closer to the observed behavior compared to the logit model (especially in the 4th and 7th panels). The advantage of the BGT models can be attributed to their ability to better capture road user behavior by more accurately simulating the human decision-making process (Fig. 4, bottom row panels).

4. Discussion

It was found that the cyclists' kinematic (speed and distances) and non-kinematic cues (pedaling and looking towards the vehicle) were useful for predicting cyclist-vehicle interactions at unsignalized intersections (Table 7). These results are in line with the prior findings of Mohammadi et al. (2023) regarding the role of cyclists' non-kinematic cues in predicting their yielding decision at unsignalized intersections (Mohammadi et al., 2023). The cyclists' kinematic information had a larger effect size than the non-kinematic information, indicating it plays a greater role in predicting road users' intent. Therefore, automated vehicle sensors (such as LiDARs and cameras) should prioritize acquiring kinematic data from surrounding road users over other types of data. Nonetheless, vehicle sensors should also obtain information about cyclists' non-kinematic cues in order to further enhance threat assessment algorithms.

The outputs of the logit regression suggested that as the cyclist's TTA increases, it becomes less likely that the cyclist will cross the intersection before the vehicle. This correlation is reasonable, because the vehicle will have more time to cross the intersection first. Meanwhile, as the vehicle's TTA increases, it becomes less likely that it will cross the intersection before the cyclist. Similarly, as the cyclists' distance to the trajectory convergence point increases, the likelihood that they will cross the intersection first decreases. Attempts to understand e-bike behavior in vehicle interactions were limited by the scarcity of cases (three) observed.

There were clear relations between the cyclists' non-kinematic cues and their decision to cross before the vehicle. If the cyclists were pedaling at the beginning of the intersection, they were more likely to cross the intersection first. This correspondence aligns with the logic that if cyclists intend to cross before the car, they will keep pedaling without stopping. By directing their head towards the approaching motorized vehicle, cyclists are engaging in implicit communication with the driver, asserting their right of way (Grigoropoulos et al., 2022). Visual scanning holds significant importance in dynamic driving, since drivers consistently employ peripheral vision to identify potential hazards and communicate effectively with other road users. (Rasanen and Summala, Mar. 2000). Up to now, threat assessment algorithms have primarily relied on kinematic data to identify potential hazards in mixed traffic, often overlooking non-kinematic cues from other road users (Wang et al., 2021; Feng et al., 2024). The present study underscores the significance of implicit communication in predicting cyclists' intentions during crossing scenarios.

The findings of this study have significant implications for the development of AVs, particularly in the context of their interactions

Table 8
Model comparison (P = professional driver, NP = non-professional driver, and T = both type of drivers).

Model	**Logit**									**BGT**					
	Model I			Model II			Model III			Model I			Model II		
RMSE	P	NP	T	P	NP	T	P	NP	T	P	NP	T	P	NP	T
	0.226	0.188	0.143	0.246	0.174	0.138	0.218	**0.158**	0.132	0.220	0.181	0.136	**0.152**	0.171	**0.129**
AIC	195.94			193.316			170.182			197.45			**150.29**		
BIC	202.052			202.48			188.52			206.56			**162.51**		
NLL	95.970			93.658			79.091			95.725			**71.145**		
Num. of params	2			3			6			3			4		

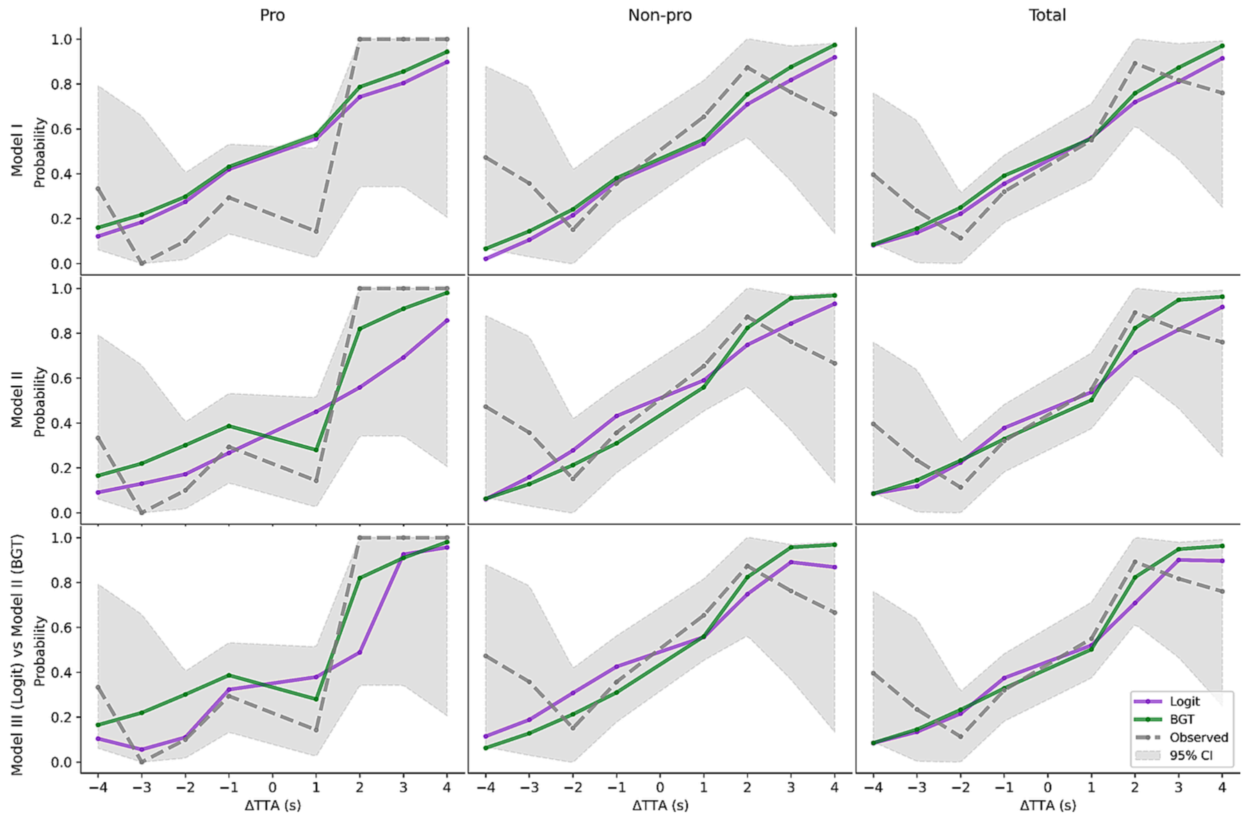


Fig. 4. Cyclists' probability of passing first over ΔTTA for all models (pro, non-pro, and total stands for professional driver, non-professional drivers, and both driver groups together).

with cyclists at unsignalized intersections. By highlighting the differences in yielding behavior between professional and non-professional drivers, the study underscores the importance of designing AV decision-making systems that can account for variations in human driving behavior. Integrating models that incorporate both kinematic and non-kinematic factors—such as cyclists' head movements and pedaling activity—into AV algorithms can enhance their predictive capabilities, enabling AVs to anticipate cyclists' intentions more accurately and respond appropriately in mixed traffic environments. Furthermore, the application of behavioral game theory in this context provides a framework for simulating realistic interactions, allowing AVs to adapt their behavior dynamically based on the actions of surrounding road users. These insights contribute to the safe and seamless integration of AVs into urban traffic systems, improving their ability to protect vulnerable road users and fostering public trust in automated mobility solutions.

AVs will coexist with human-driven vehicles for a considerable period before reaching full market adoption. During this transitional phase, many expect AVs to mimic human driving behavior so they can integrate seamlessly into traffic without causing surprises or alarm—particularly for vulnerable road users such as cyclists. In this paper, we present models that capture human behavior at intersections, thereby raising the question of which of these models might best suit AVs. While we do not provide a definitive answer, our findings show that different groups of human drivers exhibit distinct behaviors—behaviors that cyclists appear to manage regularly, even though they affect cyclists' access to infrastructure. In other words, this paper offers two potential reference models (Fagnant and Kockelman, 2015 Rasouli and Tsotsos, 2019) while emphasizing that road users are relatively flexible. Consequently, selecting a specific model for AVs may be less critical than some of the current literature (e.g., (Markkula et al., 2018) suggests.

4.1. Professional and non-professional drivers

One of the study's objectives was to quantitatively investigate the differences in how professional and non-professional drivers interacted with cyclists at unsignalized intersections. We tested the hypothesis that professional drivers are more likely to cross intersections ahead of cyclists due to their risk-taking driving behavior. The outputs from both predictive models (logit and BGT) support our hypothesis: the inclusion of the driver type parameter improved the models' performances (Table 8), indicating that it explains some of the variations in the outcome variable (yielding decision).

Fig. 4 demonstrates that professional drivers exhibit a bias toward going first at zero ΔTTA, requiring a larger TTA advantage for cyclists to reach a 50/50 probability. In contrast, non-professional drivers show a symmetric probability curve around zero ΔTTA, indicating an interaction in which both parties have an equal chance of going first.

While previous research has reported that professional drivers engage in more risky driving behaviors (Öz et al., 2010; Kalantari et al., 2023), to date no studies have compared how various groups of drivers interact with VRUs—and cyclists in particular. In this study, it was found that professional drivers yield to cyclists less often than non-professional drivers.

The observed differences in driving behaviors between professional and non-professional drivers can be attributed to a variety of factors. Professional drivers, due to their extensive time on the road, may develop overconfidence, potentially leading to riskier behaviors, yet their experience also equips them with the skills to navigate challenging situations (Nordfjrn et al., 2012). Economic incentives linked to job performance can encourage speeding or aggressive driving, a pressure less prevalent for non-professional drivers (Öz et al., 2010). Continuous exposure to road risks may also desensitize professional drivers, skewing their risk perception and fostering an underestimation of danger. Stressful work environments, characterized by tight schedules and demanding conditions, further exacerbate the risk of impaired judgment. Lastly, the influence of societal and cultural norms within the professional driving community often lead to a higher propensity for risk-taking, setting them apart from non-professional drivers who generally exhibit more cautious behavior. Collectively, these factors may have contributed to the professional drivers' distinctive driving behaviors and attitudes towards risk. It has already been suggested that training programs, enhanced regulations, and increasing awareness of the risks described above may improve the safety awareness of professional drivers. The findings of this study can enhance those efforts (Wu et al., 2016). Even though there are inherent differences in vehicle size, dynamics, and visual constraints between trucks and taxis, we classified them together primarily due to their shared status as professional drivers—i.e., individuals with higher on-road exposure and potentially greater risk-taking tendencies (Galal et al., 2024). While this approach inevitably obscures some distinctions unique to each subgroup, our limited sample size constrained a more granular analysis. Consequently, we focused on capturing the broader effect of professional driving behaviors, acknowledging that future research with larger datasets could more thoroughly distinguish these vehicle types and their associated risks.

4.2. Modeling outputs

This paper introduces predictive models that can determine which road user is likely to cross an unsignalized intersection first in a cyclist-vehicle interaction, providing the vehicle with sufficient lead time to react safely, either by yielding or taking evasive action. Thus, automated vehicles can respond safely to similar encounters with cyclists. Logit regression was used to identify the variables affecting the interaction outcome; in the next phase, we aimed to investigate the prediction accuracy by employing both logit and BGT models. As highlighted earlier, BGT models have previously demonstrated their efficacy as a potent tool for capturing the interactions between vehicles and pedestrians (Kalantari, 2023).

Table 8 demonstrates that the BGT Model II outperformed the logit models in terms of AIC, BIC, and RMSE. Three logit models were developed with either two, three, or five variables, for comparison. Models I and II used the same variables in both the logit and BGT models to ensure a fair comparison. While BGT Model I performed similarly to logit Model I, the BGT model with two variables outperformed all logit models, including the full model with five variables. This distinction shows that adding the driver type variable significantly enhanced the model's performance. Additionally, the results in Table 8 demonstrate that the BGT model captures the non-linear effect of kinematic parameters on interaction outcomes more effectively than the logit model. The improvement in fit from Logit model II to BGT model II is more substantial than that observed when non-kinematic predictors are added to the same type of model, as seen when comparing Logit model II to Logit model III. Although incorporating non-kinematic predictors into the BGT model presents a challenge in terms of defining payoff formulation, doing so might enhance the model's performance even further. As a result, BGT models could better capture the variations in the outcome variable and account for the non-linearity of the independent variables.

Our findings suggest that BGT models applied to interactions between vehicles and cyclists can provide a deeper understanding of road user behavior, which can be implemented in vehicle automation. However, developing complex BGT models presents challenges, such as achieving proper model convergence and constructing a comprehensive payoff matrix. In contrast, logistic regression models are generally easier to integrate with various types of variables.

Both accuracy and interpretability are crucial in active safety systems and automated vehicles to reduce false positive and false negative predictions. Machine-learning models are the primary approach for decision-making and motion-planning algorithms in the automotive industry; however, their reliance on large datasets introduces issues such as bias and accidental correlations (Wang et al., 2021). Resolving these issues is challenging due to the opacity and non-linear nature of the algorithms. On the other hand, this study shows that more interpretable models, particularly BGT models, can perform well even with small datasets, providing researchers with detailed insights into road user behavior (Kalantari, 2023).

4.3. Limitations

The decision-making process in road interactions involves many factors, such as the state of road users (including fatigue and attention) and infrastructure design, that this study did not capture due to data limitations. It is also important to note that the trajectory lengths of the interacting road users, particularly the motorized vehicles, were limited—it was unclear when they started reducing speed as they approached the intersection. Further, despite attempts to filter out noise in the speed profiles, accelerations derived from noisy speeds were deemed unreliable, so variables like road user deceleration rates were not included in the models.

As outlined in the methodology, the study focused solely on interactions between motorized vehicles and cyclists in the absence of other road users. However, real-world scenarios can be more intricate, with simultaneous multiple interactions. Furthermore, while collecting data from diverse locations could have enhanced the models' generalizability and accuracy, we limited data collection to a single location due to the time-consuming manual coding required.

Suggestions for improving model performance include observing more interaction events and collecting data from multiple locations. Another recommendation is to incorporate deceleration rates as predictors in the model. Obtaining more precise and extended kinematic data (which would permit the inclusion of jerk) from interacting road users would facilitate a deeper understanding of yielding phenomenon, ultimately leading to more robust and reliable models.

This study advances our understanding of cyclist-vehicle interactions at unsignalized intersections, providing critical insights to improve predictive models and enhance the safety and efficiency of automated vehicles.

5. Conclusions

In this study, we aimed to enhance the understanding of cyclist-vehicle interactions at unsignalized intersections, driven by three primary objectives. First, we sought to model which agent (cyclist or vehicle) crosses first using both logit and BGT models. Second, we explored how these interactions differ between professional and non-professional drivers. Lastly, we compared the effectiveness of these models in predicting cyclists' crossing decisions. Our hypotheses were that BGT models would outperform logit models and that professional drivers would yield less often than non-professional drivers. These hypotheses were confirmed, providing deeper insights into the dynamics of these critical road interactions.

Our study revealed that professional drivers exhibit a lower likelihood of yielding to cyclists than do non-professional drivers. Professional drivers showed a clear tendency to go first at zero ΔTTA; cyclists required a larger TTA advantage to reach an equal probability. In contrast, the symmetric probability curve around zero ΔTTA for non-professional drivers indicates a fairer interaction—both parties have an equal chance of going first. This discrepancy suggests that regulations and training programs should be specifically designed to address the behavior of professional drivers in order to improve cyclists' safety. Finally, whether such training should be different for professional car drivers, such as taxi drivers, and truck drivers is still an open question since our dataset did not allow for this analysis.

Notably, both kinematic parameters (speed and distances) and cyclists' non-kinematic cues are crucial for predicting cyclists' decisions to yield at unsignalized intersections. While kinematic parameters have a larger effect on the interaction outcome, integrating both kinematic and non-kinematic information can improve threat assessment algorithms and better enable automated vehicles to anticipate cyclists' choices at intersections.

The logit regression identified significant variables affecting cyclists' crossing decisions, including cyclist TTA, vehicle TTA, cyclist distance, looking towards the approaching vehicle, and pedaling. These variables provide valuable insights into the dynamics of cyclist-vehicle interactions, influencing the likelihood of yielding at intersections. More importantly, employing BGT models enhanced prediction accuracy, demonstrating their efficacy in capturing the non-linear relationships between variables. In the context of active safety systems and automated vehicles, achieving higher prediction accuracy is paramount to avoid false positives and negatives. Therefore, our study suggests that BGT models can be a valuable tool for modeling complex vehicle-cyclist interactions, contributing to the development of advanced safety systems in the realm of automated vehicles.

CRediT authorship contribution statement

Ali Mohammadi: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Amir Hossein Kalantari:** Writing – review & editing, Visualization, Methodology, Formal analysis. **Gustav Markkula:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Marco Dozza:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization.

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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Data availability

The authors do not have permission to share data.

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