Modeling vehicle-cyclists' interactions to support automated driving and advanced driving assistance systems

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Research Article

Modeling vehicle-cyclists' interactions to support automated driving and advanced driving assistance systems☆

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ABSTRACT

Cycling has gained increasing popularity across Europe, yet the frequency and severity of cyclist-vehicle conflicts at unsignalized intersections remain key road-safety concerns. This study investigates the interaction between drivers and cyclists in such settings, focusing on the role of intersection visibility (IV), difference in time to arrival (DTA) of the car and bicycle, and drivers' gaze behavior in shaping yielding decisions, braking patterns, and speed profiles. Using a driving simulator equipped with eye-tracking technology, participants completed multiple drives through the digital twin of a real-world intersection. The IV was systematically varied by repositioning a parked truck, while the DTA was controlled by triggering the virtual cyclist's approach at different temporal offsets relative to the car's arrival.

Mixed-effects Bayesian regression models revealed that both IV and DTA significantly influenced the drivers' likelihood of yielding: higher visibility and a shorter time difference between vehicle and cyclist arrivals consistently increased yielding rates. Gaze behavior also emerged as a critical factor; earlier fixation on the crossing cyclist strongly correlated with the likelihood of deciding to yield. In contrast, no single predictor significantly explained the distance at which drivers initiated braking. Speed-profile analyses further underscored the finding that drivers' deceleration strategies are shaped by visibility constraints and perceived temporal pressure from oncoming cyclists.

These findings highlight the importance of visibility, temporal cues, and visual attention metrics in intersection designs and advanced driver assistance systems. Safety technologies and automated features can more accurately anticipate driver-cyclist interactions when gaze behavior is integrated into their predictive models. Future work should confirm these insights through on-road studies, as well as exploring additional intersection layouts and environmental conditions to obtain more data that can lead to enhance both infrastructure design and automated vehicle algorithms.

1. Introduction

The popularity of cycling as a mode of transportation has been steadily increasing across Europe, offering numerous benefits such as reduced traffic congestion and improved public health [1]. However, this surge in cycling activity has also exacerbated the critical need to ensure cyclist safety in urban areas where interactions with motor vehicles are frequent [2]. European statistics reveal a concerning trend: while fatalities among motor vehicle occupants are declining, the proportion of cyclist fatalities is on the rise [3]. Unsignalized intersections, in particular, have been identified as hotspots for conflicts between cyclists and drivers, often due to miscommunication or ambiguous right-of-way rules [4,5].

Advancements in active safety systems and automated vehicles (AVs) offer promising solutions for improving interactions between cyclists and motor vehicles [6]. The widespread adoption of AVs has the potential to reduce conflicts by eliminating human driver errors; however, AVs must be adept at safely navigating complex urban environments and interpreting the behaviors of vulnerable road users (VRUs) like cyclists [7]. For AVs and advanced driver assistance systems (ADAS) to function optimally, they need to accurately interpret the intentions of VRUs [8]. According to Aust et al. (2023), active safety systems have three phases:

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detection, decision-making, and intervention [9]. The detection phase involves collecting data via vehicle sensors, the decision-making phase processes this information to assess potential risks, and the intervention phase executes appropriate actions (ranging from driver warnings to autonomous maneuvers). Understanding the nuanced dynamics of driver-cyclist interactions is essential for these systems to make informed decisions and intervene appropriately.

Despite research on driver-cyclist interactions, significant gaps remain in understanding factors like limited visibility at intersections and timing discrepancies between road users, as well as how environmental and temporal variables affect drivers' decision-making [10]. For instance, Silvano et al. (2016) conducted field observations at unsignalized crossings and developed probabilistic models to predict cyclists' yielding behavior based on kinematic variables like speed and distance, finding that time to arrival and vehicle speed significantly influenced cyclists' decisions to yield. However, their research primarily focused on roundabouts and did not capture drivers' detailed trajectory data, limiting the applicability of their findings to other intersection types [5].

Bella and Silvestri (2018) utilized a driving simulator to examine how different infrastructure designs impact drivers' responses when interacting with cyclists, applying infrastructural modifications such as pavement markings and raised islands. While their findings highlighted the role of infrastructure in enhancing safety, they did not delve into the influence of visibility or timing factors on drivers' yielding decisions [11]. Similarly, Velasco et al. (2021) employed virtual reality to study cyclists' crossing decisions in the presence of approaching vehicles, focusing on factors like gap distance and right-of-way priority from the cyclists' perspective. These studies, while valuable, have not examined the drivers' behavioral responses under varying conditions of visibility and timing at unsignalized intersections [12].

Driving simulators have become indispensable tools for investigating driver behavior in controlled environments, enabling researchers to systematically manipulate variables and repeat complex traffic scenarios without endangering participants [13,14]. The resulting homogeneous datasets for specific traffic situations enhance the reliability of behavioral analyses [15,16]. While simulators have been extensively utilized to study overtaking maneuvers involving cyclists, there remains a paucity of research employing them to explore driver-cyclist interactions at unsignalized intersections under varying conditions of visibility and timing. Boda et al. (2018) are among the few who have investigated this area, identifying cyclist visibility as a key factor influencing driver responses. However, their study did not comprehensively examine how intersection visibility (IV) and difference in time to arrival of the two road users (DTA) affect drivers' yielding behavior and braking decisions, nor did they incorporate gaze behavior into their analysis [13].

Recent research has also highlighted the importance of visual communication cues and gaze behavior in road user interactions [17,18]. Implicit signals such as eye contact, head movements, and other aspects of body language are crucial for conveying intentions and ensuring mutual understanding between drivers and cyclists [19,20]. Eye-tracking technology provides valuable insights into drivers' visual attention and hazard perception, shedding light on the cognitive processes underlying decision-making during interactions with cyclists [12,21]. Despite the potential benefits, the integration of gaze behavior into predictive models for driver-cyclist interactions remains relatively underexplored.

The chosen interacting scenario in this study is one of the most common types of conflicts between motorized vehicles and cyclists at unsignalized intersections, namely when both road users travel straight through the intersection. Previous crash and conflict analyses have shown that straight-going vehicle–cyclist interactions, together with right-turning vehicle versus through-going cyclist conflicts, account for a large share of bicycle–vehicle crashes in urban environments [22–25]. The straight–straight scenario provides a representative yet controlled context to study the influence of visibility, timing, and gaze behavior on driver decision-making. Although right-turning maneuvers are also known to be hazardous for cyclists due to limited driver attention to the right side [26,27], we selected the straight-going interaction to align the simulated geometry with a real unsignalized intersection previously observed in our naturalistic data. This design choice allows for direct comparison between the simulator results and real-world observations, enhancing the ecological validity of the study.

The present study aims to investigate the driver's response process during interactions with cyclists at unsignalized intersections. Utilizing a driving simulator equipped with eye-tracking technology, we aim to (1) analyze drivers' responses under varying IV and DTA conditions; (2) quantify how IV, DTA, and gaze behavior influence drivers' yielding decisions, braking onset, and speed profiles; and (3) enhance our understanding of driver behavior to inform the development of predictive models. This research contributes to improving active safety systems and infrastructure design, thereby enhancing cyclist safety.

2. Materials and methods

2.1. Participants

Fifty-eight people participated in the study by driving into a simulated intersection that they negotiated with a virtual cyclist. The inclusion criteria for this experiment were: participants drive a car at least once a week, have a driving license, do not have any physical disabilities, and do not wear prescription glasses. We excluded participants who wear prescription glasses because the eye-tracking system uses goggles. We specifically targeted people with cycling experience with an additional criterion of cycling at least once a week, to ensure that the participants were familiar with cycling. Participants were recruited through online advertisements through internal email list and by contacting individuals who had participated in previous experiments. All participants signed a consent form prior to participation in the experiment.

2.2. Driving simulator and experimental setup

The driving simulator (Fig. 1) was developed by TME (Toyota Motor Europe), and the experiment was carried out in Brussels, Belgium. The 3D environment was built using CarMaker, and rFpro was used as the simulation software. The simulated environment was displayed through video projection, creating a 180-degree field of view for an immersive visual experience. The eye-tracking goggles (Tobii Pro Glasses 2) worn during the experiment recorded gaze data.

In the experiment, all participants were asked to drive in the simulator, entering the intersection and turning right (as shown in Fig. 2a-b). Before the experiment, participants were informed that they would

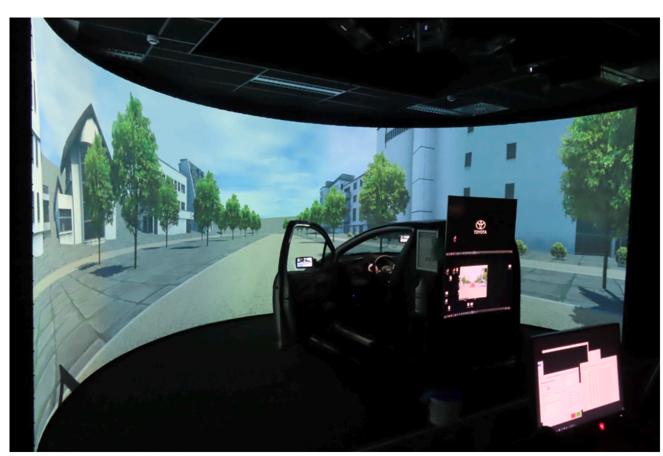

Fig. 1. Driving simulator with 180° field of view.

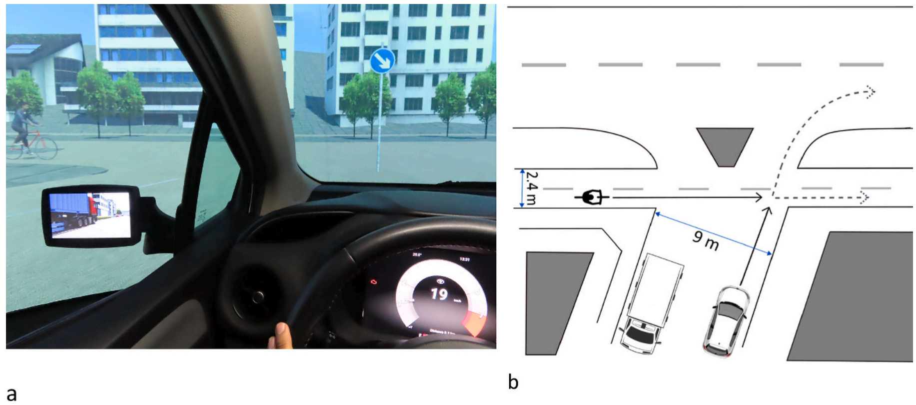

Fig. 2. Layout of the intersection simulated in the experiment: (a) driver's view of the intersection; (b) top view of the intersection, including truck obscuring visibility and arrows indicating the moving direction of the road users.

interact with a cyclist approaching from the left side of the intersection. The intersection was a digital twin of an actual intersection in Gothenburg, Sweden (GPS coordinates: 57°42′31.1"N, 11°56′22.9″E). According to traffic rules, bicycles have the right of way at unsignalized intersections, although they are still expected to be cautious and aware of surrounding vehicles. Participants were instructed to drive and behave as they normally would in real traffic. They crossed the intersection 11 times during the experiment; they first completed a test trial to familiarize themselves with the driving simulator and practice turning and braking. In the trials, they started driving 350 m away from the intersection, and they were told not to exceed the maximum allowable speed in urban areas (30 km/h). A trigger activated the virtual cyclist, which approached the intersection from the left side when the car was 100 m from the intersection. The cyclist's speed when it was first visible to the driver was set to 15 km/h and it gradually decreased following a polynomial deceleration profile, slowing to 8 km/h as the cyclist approached the intersection. These speeds were based on field observations from the actual intersection. A truck was parked at the corner of the intersection to obstruct the driver's view (Fig. 2b); its position was changed across trials to create different IVs. The IV was one of the study's independent variables, representing the distance between the cyclist and its projected point of intersection with the car when the cyclist first comes into view.

The DTA is the other independent variable in this experiment; it is the time difference between the two road users' projected arrivals at the intersection point based on their trajectories. To calculate the DTA, we assumed each road user maintained the speed they were traveling at when entering the intersection.

A full factorial design was applied, in which the DTA had three levels (0.5 s, 1 s, and 1.5 s) and the IV had two (22 m and 27 m). The vehicle always arrived first at the intersection. There were two trials with empty intersections (no cyclist), and three additional trials in which the cyclist approached the intersection from the right side. In these three trials, the truck was parked at the corner of the intersection with an IV of 22 m. The additional five trials were designed to reduce participants' expectancy of a cyclist approaching from the left and were not part of the analysis. The complete configuration of 11 trials per participant is shown in Table 1. All trials (except for the two with empty intersections) were randomized into four groups, with each group following a specific order of trials.

Table 1
Configuration of trials (* indicates trials used for the analysis; NA = not applicable).

Trial number	DTA(s)	IV (m)	Trial description
1*	0.5	22	Cyclist from left side
2	1	22	Cyclist from right side
3*	1	22	Cyclist from left side
4	NA	22	Empty intersection
5*	1.5	22	Cyclist from left side
6	1	22	Cyclist from right side
7*	0.5	27	Cyclist from left side
8	NA	22	Empty intersection
9*	1	27	Cyclist from left side
10	1	22	Cyclist from right side
11*	1.5	27	Cyclist from left side

2.3. Data analysis

2.3.1. Driver's yielding decision

A mixed-effect Bayesian logit regression was used to model the drivers' yielding decisions. The model combines fixed and random effects in a hierarchical framework [28]. Incorporating both population-level and individual-level variability enhances the flexibility and robustness of the model, particularly for complex data structures.

The observed data y_{ij} for individual i in group j are modeled as:

$$y_{ij} = \beta_0 + \sum_{k=1}^{p} \beta_k x_{ijk} + u_i + \varepsilon_{ij} \tag{1}$$

Here, y denotes the binary outcome variable representing whether the driver yielded (0) or not (1). Where β_k are fixed effect coefficients, x_{ijk} are predictors, u_i are random effects ($u_i \sim \mathrm{N}(0, \sigma_u^2)$), and ε_{ij} are residual errors ($\varepsilon_{ij} \sim \mathrm{N}(0, \sigma_u^2)$) (McElreath, 2018).

In the Bayesian framework, priors are placed on the parameters:

$$\beta_k \sim \mathrm{N}\,(0, 1000) \tag{2}$$

The variance of the random effects (σ_u) and the residual errors (σ_e) are assigned half Cauchy priors:

$$\sigma_u \sim \mathrm{Half-Cauchy}\,(0, 5) \tag{3}$$

$$\sigma_e \sim \mathrm{Half-Cauchy}\,(0, 5) \tag{4}$$

The half-Cauchy distribution is chosen because it is a weakly informative prior that constrains the variances to be positive and allows a wide range of possible values centered around 0 with a scale parameter of 5. The Normal (0, 1000) prior on regression coefficients ensures that large effect sizes are not unduly penalized, while the Half-Cauchy (0, 5) priors for variance components are standard in hierarchical Bayesian modeling, providing stability [29] and robustness without exerting strong influence. Bayesian inference was performed using Markov Chain Monte Carlo (MCMC) methods, updating prior distributions with observed data to obtain posterior distributions [30]. The posterior distribution is given by:

$$\mathrm{p}(\theta|\mathrm{y}) \propto \mathrm{p}(\mathrm{y}|\theta)\, \mathrm{p}(\theta) \tag{5}$$

This provides a full probabilistic description of the model parameters, allowing for direct probabilistic interpretation and uncertainty quantification. We applied weakly informative default prior distributions across all variables.

2.3.2. Learning effect

Because our experimental protocol was repetitive, we were concerned about a learning effect (the participants changing their behavior over time based on the previous trials). Since the trials were randomized between participants, trials were ordered differently for different groups of participants. Trial order was therefore added as a variable to the yielding-decision model, to check if it had any effect on a driver's yielding decisions.

2.3.3. Gaze data analysis

The metrics used to analyze the gaze data comprised: 1) time to the area of interest (AOI) measured from the start of each trial, 2) total number of fixations to the AOI, and 3) duration of the first fixation to the AOI. (In this study, the AOI refers to the crossing cyclist as the driver approaches the intersection.) To measure the time to the AOI, we recorded the time it took for each participant to detect the cyclist from the onset of the trial. Gaze data were extracted, and AOIs were defined around the cyclists using Tobii Pro Lab software.

2.3.4. Drivers' braking onset model

Bayesian mixed-effects regression models were employed to estimate the impact of independent variables on the longitudinal distance at which drivers initiated braking. The adoption of a Bayesian mixed-effects regression framework for braking onset was deemed appropriate because braking distance is influenced by both population-level trends (e.g., visibility, DTA) and individual variability in driving style. The hierarchical structure allows us to capture these multiple sources of variation, while the Bayesian framework provides full posterior distributions, enabling direct quantification of uncertainty. This modeling choice is consistent with prior applications in traffic behavior research [29,31]. These models incorporate fixed effects representing population-level relationships, along with random effects that account for individual variability (or group-specific differences). The general form of a Bayesian mixed-effects model is presented in Eq. 1, where y denotes the response variable, X is the design matrix for fixed effects, β is the vector of fixed effects, Z is the regressor matrix for random effects, α is the vector of random effects, and ϵ is the observation error vector.

$$y = X\beta + Z\alpha + \varepsilon \tag{6}$$

2.3.5. Modeling speed profiles

Drivers' speed profiles were modeled over time as they approached the intersection. Each individual driver's profile was fitted using an arctangent function with four coefficients. The equation includes three scaling parameters (a, b, and c) and an offset parameter (d). The average speed profile for each trial was represented by the mean speed profile with a related 95% confidence corridor. The fitting was performed using MATLAB's fit function, employing the least absolute residual method to minimize the impact of outliers. The equation used to fit the speed profiles is as follows:

$$Y = a^{*}\arctan(b^{*}t + c) + d \tag{7}$$

Where Y represents the speed, and t denotes time.

2.4. Questionnaires

To gather information about participants' experiences during and after the experiment, as well as their demographic data, two questionnaires were used. The first was the Misery Scale (MISC) questionnaire, designed to quantify the extent to which participants were affected by motion sickness [12]. The scale ranges from 0 to 10, with 0 indicating no symptoms and 10 representing severe symptoms, including vomiting. Participants were asked to report their level of motion sickness after passing through each intersection, and at the end of the experiment. The second questionnaire focused primarily on demographics and participants' experiences in the simulator. Two open-ended questions were posed at the end of the experiment to capture how the participants experienced the virtual environment: "How would you compare the scenario to real life?" and "How can we improve the simulator?"

3. Results

3.1. Descriptive statistics

A total of 58 participants enrolled in the experiment, with an average age of 31.6 years (SD = 6.2) and 34% female representation. Since 33 of the participants felt mild levels of motion sickness during the early stages of the experiment and did not complete all trials, data from 25 participants were used for analysis and modeling. The average age of this group was 32 years (STD = 6.5) with 20% female representation.

Before presenting the model-based analyses, basic behavioral results were examined to characterize participants' responses across visibility and timing conditions. Under low-visibility conditions, several drivers either failed to detect the cyclist or fixated on them with noticeable delay. These delayed detections were often associated with non-yielding outcomes. Conversely, earlier fixations and shorter detection times were more frequent when intersection visibility was high or when the cyclist's arrival time was closer to that of the vehicle. These trends are consistent with previous research showing that limited visibility and suboptimal visual scanning increase the likelihood of missed cyclist detections [12,17].

3.2. Drivers' yielding-decision model

A set of variables extracted from the sensor data, gaze data, and questionnaires was used to analyze the drivers' yielding decisions. These variables consisted of vehicle's speed at interaction onset, IV, DTA, age, braking (Y/N) at the interaction onset, gender, trial order, and time to the AOI (crossing cyclist). Three metrics from gaze data were extracted: time to the AOI, total number of fixations toward the AOI, and duration of first fixation toward the AOI. These variables are shown in Table 2. These variables were included as candidate predictors in the Bayesian regression, where their estimated coefficients represent the relationship between each factor and the binary outcome of yielding. The vehicle's

Table 2
Variables tested in the models.

	Variable	Unit	Type	Description
1	Vehicle's speed	m/s	Continuous	Vehicle's speed at interaction onset
2	DTA	S	Continuous	Difference in time to arrival at the intersection
3	IV	m	Discrete	Intersection visibility
4	Age	years	Continuous	Age of the participant
5	Gender	Dummy	Categorical	Gender (male or female) of the participant
6	Braking	Dummy	Categorical	Braking or not at the interaction onset
7	TAOI	ms	Continuous	Time to the AOI
8	Number of fixations to AOI	(No unit)	Continuous	Total number of fixations to the AOI
9	Duration of first fixation to AOI	ms	Continuous	Duration of first fixation to the AOI
10	Trial order	(No unit)	Continuous	The cardinal number indicating the order of the trial
11	Cycling experience	Nominal	Categorical	Participant's experience in cycling (1 cycling occasionally, 2 cycling regularly, 3 cycling frequently, 4 cycling daily)

speed was captured at the interaction onset, when the cyclist was first visible to the driver. Time to the AOI is the time it took for the participant to notice the cyclist from the trial start.

Summary statistics of the data used for the yielding-decision model are shown in the Table 3.

Fig. 3 shows the posterior distributions of four significant variables from the Bayesian analysis, illustrating the most probable values for each variable based on the posterior estimates across four Markov Chain Monte Carlo (MCMC) chains. The horizontal axis represents the values of the regression coefficients obtained from the posterior samples. The overlapping distributions across chains indicate good convergence. An increase in IV is associated with a higher probability that the driver will yield to the cyclist. Similarly, a shorter DTA makes it more likely that the driver will yield. In contrast, the faster the approaching vehicle's speed, the lower probability that the driver yields to the cyclist. Additionally, a shorter time to first fixation on the AOI indicates a greater likelihood that the driver will yield. These relationships highlight key factors influencing the driver's yielding behavior in interactions with cyclists. Overall, the smooth and overlapping density plots across all chains imply effective mixing and convergence, making these posterior estimates reliable. The results showed no significant influence of trial order on the likelihood of yielding, indicating that participants' behavior remained stable across repeated trials. The distinct peaks in each distribution suggest that these variables play a significant role in the model, with clear, stable posterior values produced by the Bayesian estimation.

The posterior predictive plot comparing the observed outcomes (y) and model-generated replicated outcomes (y_rep) is shown in Fig. 4. This plot illustrates the model's accuracy in predicting the probability of the binary outcome (yielding) across the range of predicted probabilities. The dark line represents the density of observed outcomes, while the lighter lines represent the density of simulated outcomes drawn from the posterior predictive distribution. The alignment between y and y_rep indicates the model's ability to replicate observed patterns in the data. A close match between these densities suggests that the model captures the underlying data structure effectively. This visual check helps assess the model's predictive performance and ensures it aligns with observed real-world outcomes.

3.3. Drivers' braking distance model

The outputs of the driver's braking-distance model did not reveal any predictor with a credibly non-zero effect on the distance at which drivers initiated braking. However, the variables DTA, vehicle speed at interaction onset, and TAOI showed posterior distributions that approached the credibility threshold, indicating suggestive but not conclusive evidence of an effect. Their posterior densities are shown in Fig. 5.

3.4. Modeling speed profiles

Eq. (7) was applied to all successfully completed trials in the analysis (Trials 1, 3, 5, 7, 9, and 11; see Table 1). The time axis in Fig. 6 is normalized between 0 and 1, where 0 represents the point 15 m from the intersection, and 1 indicates the point at which braking ceased. Table 4 provides a summary of the modeling results for the six trials. Fig. 7 demonstrates that the DTA significantly influences driving behavior at intersections. When the car arrives much earlier (higher DTA; Trial 5), drivers exhibit greater speed variability and maintain higher speeds. When the arrival times are closer (lower DTA; Trial 1), drivers adopt more consistent and cautious behaviors, likely prioritizing safety in the interaction scenario. Drivers appear to vary their speeds more when visibility is greater, possibly due to increased confidence and time to adjust based on other factors (Fig. 8). In contrast, lower visibility may constrain drivers to adopt a more uniform and cautious approach to maintain safety.

Table 3
Summary statistics of all continuous variables, presented as the mean (standard deviation)[range of values].

Variable	Statistics
Vehicle's speed (m/s)	4.86 (1.98) [1.25, 9.7]
TAOI (ms)	3837 (4002) [0, 11118]
Number of fixations to AOI	0.913 (1.38) [0, 5]
Duration of first fixation to AOI (ms)	118 (210.4) [0, 1535]
Trial order	5.72 (3.57) [1,11]
Cycling experience	1.35 (1.69) [0, 4]

3.5. Questionnaire data

The first questionnaire revealed that the average MISC score at the end of the experiment was 3.43 (SD = 1.84) out of 10 (0–10). This indicates that participants generally experienced a level of motion sickness they considered tolerable by the end of the experiment. Participants were asked how their experience of the scenario compared to real life, and the majority (36%) reported that the scenario felt realistic. However, several areas for improvement were identified: 32% of respondents highlighted a lack of communication and eye contact with the cyclist, and 20% suggested the need for better environment graphics. Additionally, 24% noted the absence of other road users, while 20% pointed out that the cyclist's speed could be more realistic when crossing the intersection. A less common, but notable, concern was that braking and steering felt unrealistic (12%). These insights suggest that while the scenario was generally perceived as realistic, enhancing specific elements could improve the simulation's fidelity, user experience, and validity of the results.

Participants provided several suggestions for improving the driving simulator, with nearly 40% emphasizing the need to enhance braking and steering to better mimic real-world driving conditions. Other notable suggestions include improving the environment design and addressing unrealistic cyclist behavior, both mentioned by 32% of respondents. Additionally, 24% highlighted the need to add more road users, while 20% pointed out issues with the mismatch between acceleration and feedback and the need for better speed control. A smaller but still noteworthy concern was the stiffness of the steering, cited by 12% of respondents. Implementing these suggestions would significantly enhance the simulator's realism and effectiveness.

4. Discussion

This study investigated driver-cyclist interactions at unsignalized intersections, focusing on how intersection visibility, time of arrival, and gaze behavior influence drivers' decisions to yield, braking patterns, and speed profiles. The findings provide novel insights for improving road safety and designing more effective active safety systems and automated driving, emphasizing the importance of enhancing visibility at intersections and integrating gaze and behavioral cues into predictive models to better anticipate driver and cyclist actions. These advancements can inform infrastructure design to create safer intersections as well as supporting the development of technologies that ensure smoother and safer interactions between AVs and cyclists.

4.1. Yielding-decision model

The yielding-decision model demonstrated that IV and DTA significantly influenced drivers' decisions to yield. Higher visibility distances allowed drivers to perceive and react to approaching cyclists earlier, increasing the likelihood of yielding. This result aligns with findings from Bella and Silvestri (2018), who showed that improving intersection visibility through infrastructure changes, such as raised islands or clear sightlines, can reduce conflicts between cyclists and vehicles. Similarly, shorter DTA values, indicating that cyclists arrived at the intersection closer in time to the vehicle, prompted drivers to yield more frequently. Velasco et al. (2021) and Mohammadi et al. (2024) also found that DTA

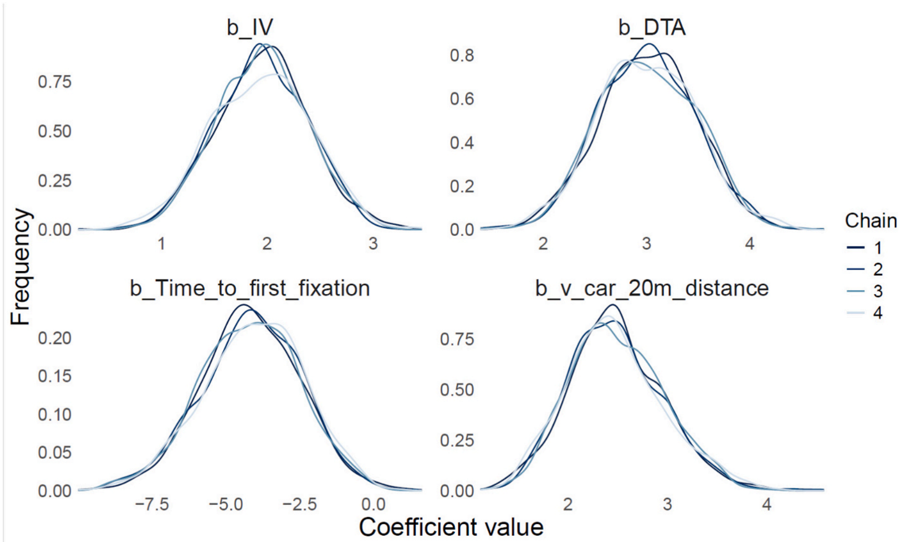

Fig. 3. Posterior density distributions for the main model parameters: b_IV, b_DTA, b_Time_to_first_fixation (TAOI), and b_v_car_20m_distance. Each panel shows the distribution of posterior samples for one parameter, with the model's predicted densities (blue lines).

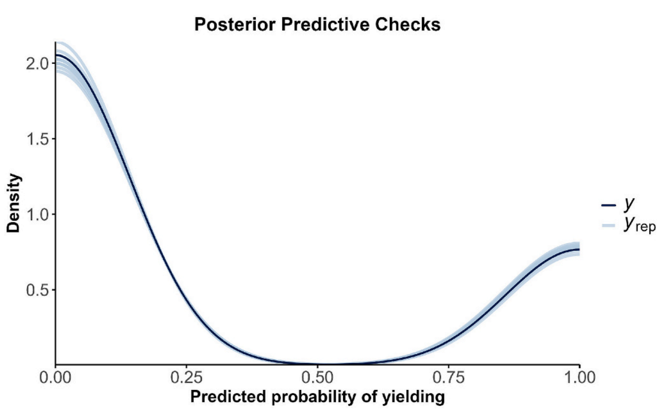

Fig. 4. Posterior predictive checks.

is a critical factor influencing decision-making in interactions between road users [12,24]. Moreover, previous naturalistic studies, such as the one by Silvano et al. (2016), demonstrated the importance of temporal dynamics, suggesting that road user behavior is highly sensitive to changes in relative time gaps during interactions at intersections.

Interestingly, gaze behavior, specifically the time to the AOI, emerged as a critical predictor of yielding decisions. The fact that drivers who fixated on the cyclist earlier were more likely to yield suggests that gaze behavior can serve as a proxy for attentiveness and hazard recognition. This possibility is supported by the finding of Hemeren et al. (2014) that visual cues, such as head movement and eye contact, are pivotal in road user interactions; they act as implicit communication tools influencing decision-making processes [17]. Moreover, Mahadevan et al. (2018) highlighted the importance of integrating explicit and implicit communication cues into interaction models to enhance prediction accuracy [18].

Integrating these findings into predictive models could significantly enhance active safety systems and AVs. For instance, incorporating gaze-based metrics into AV threat-assessment algorithms could improve the system's ability to anticipate and react to cyclists, as demonstrated Mahadevan et al. (2018) and Abadi & Goncharenko (2022), who highlighted the role of cyclists' visual cues in predicting their intent [18,32]. Additionally, previous work using naturalistic data by Mohammadi et al. (2023) found that combining kinematic and gaze metrics enhanced the predictive power of behavioral models, underscoring the potential benefits of multi-modal approaches in AV development [33].

These findings collectively suggest that enhancing visibility at intersections, emphasizing the arrival time of other road users through real-time driver assistance systems, and leveraging gaze metrics in active safety systems could lead to safer and more predictable interactions between drivers and cyclists.

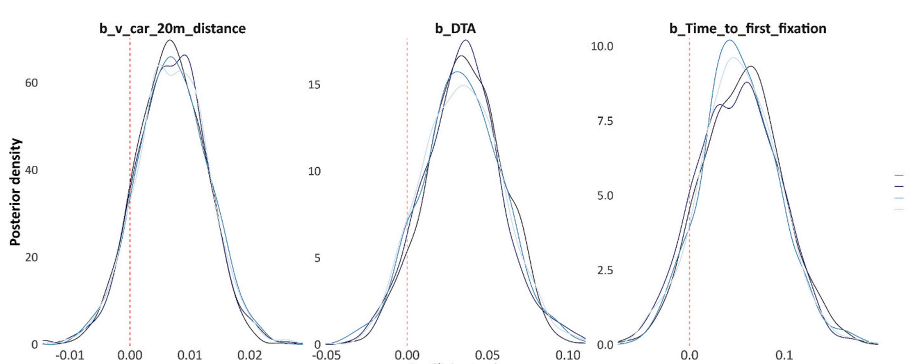

Fig. 5. Posterior distribution of selected parameters for brake distance model.

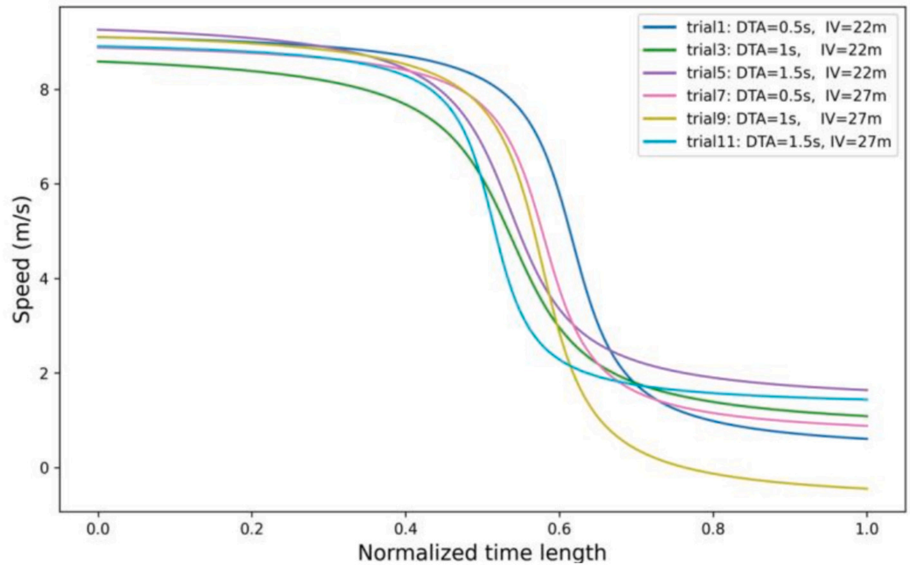

Fig. 6. Drivers' average fitted speed profiles for the 6 trials.

Table 4
Summary of fitting results.

Trial number	Maximum slope	R^2
1	−8.88	0.966
3	−7.65	0.977
5	−8.42	0.951
7	−9.67	0.983
9	−9.95	0.984
11	−10.5	0.988

4.2. *Brake distance model*

Contrary to expectations, the brake distance model did not identify any variables with statistically significant effects on the distance at which drivers initiated braking. However, DTA, vehicle speed, and gaze metrics (such as time to the AOI) were close to the threshold of significance. A study by Boda et al. (2020) reported that drivers' braking decisions are influenced by factors such as visibility, interaction dynamics, and perceived threat levels [31]. These results together suggest that braking decisions are influenced by a complex interplay of factors not fully captured in the current experimental setup; in fact, participants may perceive less risk in a simulated environment, leading to altered braking behavior. Future work should explore the relationships further, potentially using naturalistic driving data to capture more authentic braking responses.

4.3. *Speed profiles*

Modeling the speed profiles revealed distinct patterns in drivers' deceleration as they approached the intersection. Shorter DTAs led to earlier and more gradual decelerations, while higher IVs encouraged drivers to adjust their speed earlier. These findings emphasize the importance of both temporal and spatial factors in shaping driving behavior, consistent with the studies by Mohammadi et al. (2024) and Bella & Silvestri (2018) on road users' responses to infrastructure design [11,24].

The use of an arctangent function to model speed profiles provided a robust representation of the average deceleration patterns, highlighting the utility of this approach for understanding dynamic interactions at intersections. From a practical perspective, these findings suggest that improving visibility and implementing dynamic signage or adaptive signal control systems that adjust based on real-time cyclist detection could encourage earlier and more controlled deceleration, thereby reducing the likelihood of abrupt braking and unsafe interactions at intersections.

4.4. *Participant perceptions*

The questionnaire responses provided novel and valuable qualitative

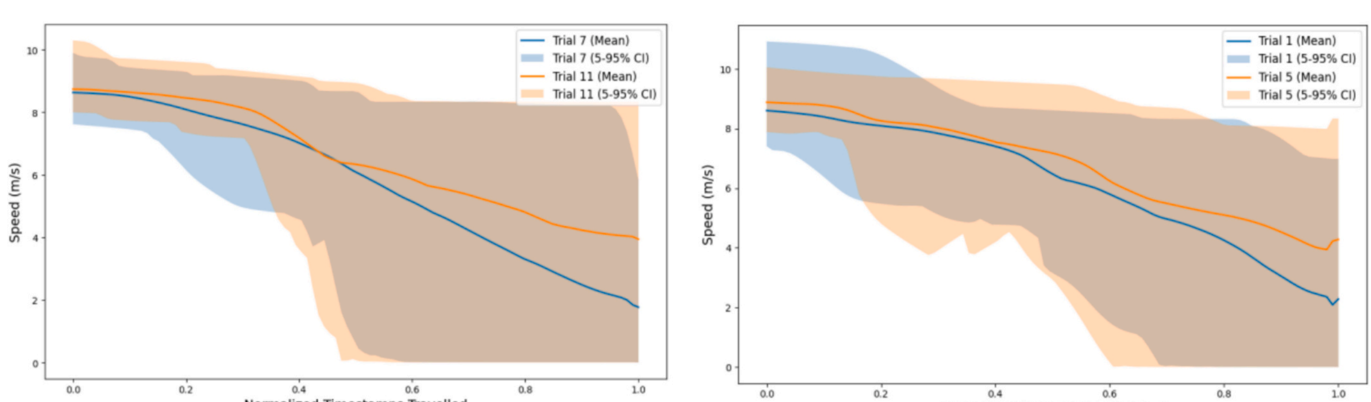

Fig. 7. Comparison of trials with same IV and different DTA.

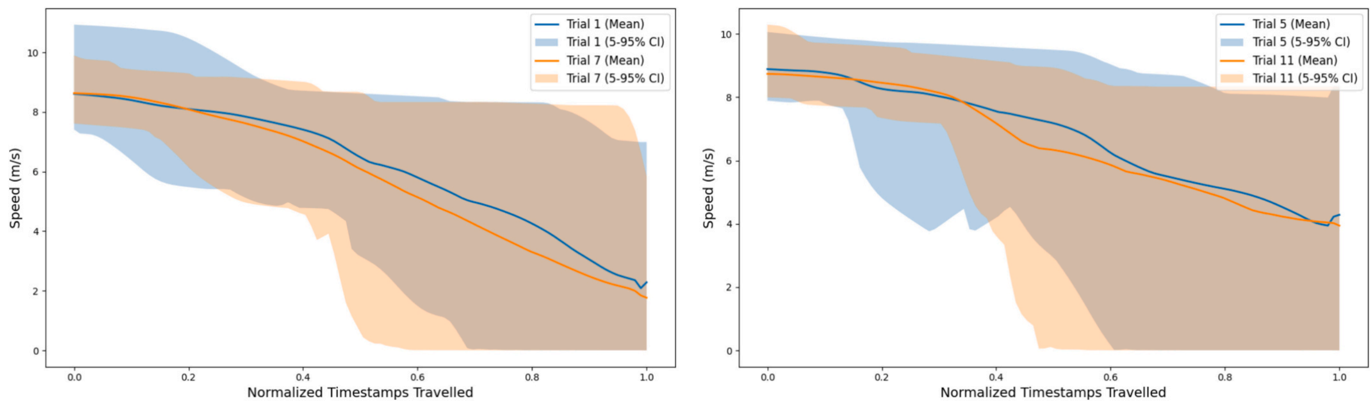

Fig. 8. Comparison of trials with same DTA and different IV.

insights into participants' experiences. Most participants noted that the simulator scenario felt realistic but highlighted specific areas for improvement, such as better communication with cyclists and enhanced braking feedback. The absence of eye contact or explicit communication with the cyclist was frequently mentioned, underscoring the importance of visual interaction in shaping driver behavior. This observation aligns with prior research by Mahadevan et al. (2018), which emphasized the role of implicit and explicit communication cues in road user interactions [18].

These findings have implications for both simulation design and real-world safety systems. Incorporating more realistic cyclist behaviors, such as gestures or gaze direction, into simulation scenarios could improve the ecological validity of future experiments. Additionally, AVs and safety systems could benefit from algorithms that account for these communication cues to better predict cyclist intent.

4.5. Limitation and future works

This study has several limitations. First, the participants' demographics, inducing age and gender lacked sufficient diversity to accurately represent the community. A driving simulator, while providing a controlled environment, may limit the ecological validity of the results, as participants may behave differently than in real-world settings. As noted, participants may be less cautious, and brake differently. Further, the lack of implicit communication cues, like eye contact or gestures, from the virtual cyclist could also influence driver behavior. Additionally, the generalizability of the results may be limited by the low sample size, further reduced from the original number by participant dropouts due to motion sickness. Although the final sample size was reduced due to motion sickness, the remaining data were sufficient for credible model estimation. Nevertheless, smaller samples increase uncertainty and limit generalizability. Future studies with larger and more diverse participants are needed to validate and extend these findings. Finally, the study focused on a single intersection, which may not represent other layouts or traffic scenarios.

Future work could address these limitations. Ideally, future research will have access to advanced driving simulators that offer more realistic driving experiences with enhanced graphics, vehicle dynamics, and interactive elements like eye contact or gestures. Together with advanced models, such as time-series or machine learning-based approaches, this technology could more accurately capture the temporal dynamics of real-world driver behavior. The generalizability of the findings could be improved by recruiting more participants and exploring a wider range of intersections—expanding data collection to include diverse intersection layouts with varying geometries and traffic conditions. Further validating this study's findings by performing naturalistic driving studies would enable more accurate predictions and improvements in safety systems and automated vehicle algorithms.

5. Conclusions

The present study used a simulator to investigate human drivers interacting with a virtual cyclist at unsignalized intersections. The factors intersection visibility (IV), difference in time to arrival (DTA), and gaze behavior were found to influence drivers' yielding decisions, braking patterns, and speed profiles. These insights can be used to improve road safety as well as to inform the design of manual and automated driving systems. In particular, our results indicate that earlier visual detection of cyclists and a clearer understanding of their arrival times positively influence yielding decisions. Applying this information to predictive models for AVs would require additional on-road validation, to ensure that AV's sensors and algorithms can reliably respond to cyclists in the real world. Nonetheless, incorporating metrics such as IV and DTA could improve an AV's ability to assess risk, anticipate the presence of VRUs, and initiate timely interventions. In manual driving contexts, gaze data (used alongside previously established metrics) can inform the design of ADAS solutions, improving drivers' situational awareness and promoting safer interactions with cyclists, particularly in conflict-prone scenarios.

From an infrastructure design perspective, our results reinforce the importance of clear sightlines for promoting safer driver-cyclist interactions: our model shows that improving visibility from 22 m to 27 m increases the likelihood of yielding—and this effect becomes more pronounced as the car and cyclist arrival times become closer (i.e., smaller DTA). By quantifying the combined impact of visibility and timing, our findings clearly identify where design interventions such as repositioning obstacles or reconfiguring approach angles could yield the greatest safety benefits. These insights extend beyond confirming a known principle (that visibility matters) by illustrating how limited sightlines in conjunction with shorter DTAs can compound the risk of conflict, and by demonstrating where targeted design changes can most effectively reduce crashes at unsignalized intersections.

Although the braking-distance model did not yield statistically significant predictors, our results indicate that braking behavior at unsignalized intersections depends on a range of interacting factors—such as visibility constraints, timing gaps, and driver attention—rather than any single variable. Likewise, the speed-profile analysis shows that drivers adjust their deceleration in response to IV and DTA, especially under low-visibility conditions or tight arrival-time gaps. However, braking alone may not serve as a reliable external cue of driver (or AV) intent. More holistic approaches, which combine subtle speed adjustments and communication channels (e.g., visual or auditory cues), may be needed to ensure that cyclists and other road users clearly understand an approaching vehicle's intentions.

A key contribution of our study is demonstrating the decisive role that gaze behavior plays in driver–cyclist interactions: earlier fixation on the cyclist strongly correlates with a higher probability of yielding, underscoring how visual attention can serve as a proxy of driver intent and hazard recognition. ADASs could be designed to monitor a driver's gaze in real time. When the driver's gaze toward a cyclist (for example) is delayed or absent, the system could infer a lapse in attention and provide a visual or auditory cue, nudging the driver to focus on the cyclist's position. By leveraging gaze-based metrics alongside other kinematic and contextual data, ADASs can support driver decision-making more proactively and reduce conflict risks at unsignalized intersections.

While existing design manuals address visibility, our findings quantitatively show how even small changes in the placement of an obstruction (e.g., a parked truck) can markedly influence drivers' detection of cyclists, thus suggesting refinements to the guidelines regarding safer unsignalized intersections. Infrastructure interventions should focus on enhancing sightlines to minimize driver-cyclist conflicts, while ADAS systems could incorporate IV, DTA, and gaze metrics to better anticipate and respond to VRUs.

CRediT authorship contribution statement

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