THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Computational models for safe interactions between automated vehicles and cyclists

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To my family

Abstract

Cyclists, as vulnerable road users, face significant safety risks in traffic, especially at unsignalized intersections where they must interact with motorized vehicles. This PhD thesis investigated bicycle-vehicle interactions at unsignalized intersections and developed predictive models to improve active safety systems and automated driving. The research integrates naturalistic and simulator data to model the behavior of both cyclists and vehicles at intersections. The models included kinematic factors, non-verbal communication, and glance behavior.

The studies included in this thesis revealed that kinematic factors, such as time to arrival (DTA), along with cyclists' non-verbal cues, like head movements and pedaling, significantly affect yielding behavior at intersections. Both simulator data and naturalistic data confirmed that visibility conditions and DTA played a critical role in cyclists' decision-making while subjective data from questionnaires highlighted the importance of communication and eye contact between cyclists and drivers in reducing the severity of interactions.

Additionally, an analysis of naturalistic data uncovered differences in yielding behavior between professional and non-professional drivers, with professional drivers being less likely to yield to cyclists. Different models, leveraging machine learning and game theory, were developed to predict yielding decisions during these interactions. Lastly, simulator data was used to model drivers' behavior, incorporating kinematics, demographics, and gaze metrics to predict drivers' responses to crossing cyclists.

The predictive models developed through this research provide novel insights for the design of threat assessment algorithms for active safety and automated driving, enhancing the machine ability to anticipate cyclist behavior and improve safety.

Keywords: automated vehicles safety, automated driving, advanced driving assistance systems, computational behavioral models, cyclist behavior, active safety systems.

Publications

This thesis is based on the following appended papers:

PAPER I Mohammadi, A., Bianchi Piccinini, G., & Dozza, M. (2023). How do cyclists interact with motorized vehicles at unsignalized intersections? Modeling cyclists' yielding behavior using naturalistic data. *Accident Analysis & Prevention, 190,* 107156. https://doi.org/10.1016/j.aap.2023.107156

PAPER II Mohammadi, A., Bianchi Piccinini, G., & Dozza, M. (2024). Understanding the interaction between cyclists and motorized vehicles at unsignalized intersections: Results from a cycling simulator study. *Journal of Safety Research*. https://doi.org/10.1016/j.jsr.2024.05.007

PAPER III Mohammadi, A., Bruneau, A., & Dozza, M. Modelling vehicle-cyclists' interactions to support automated driving and advanced driving assistance systems. *Journal of the International Association of Traffic and Safety Sciences (IATSS).* (Submitted)

PAPER IV Mohammadi, A., Kalantari, A., Markkula, G., & Dozza, M. (2024). Cyclists' interactions with professional and non-professional drivers: Observations and game theoretic models. *Journal of Transportation Research Part F: Traffic Psychology and Behavior.* (Under review)

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Contents

List of abbreviations

Abbreviation	**Full name**
AEB	Autonomous Emergency Braking
AD	Automated Driving
ADAS	Advanced Driver Assistance Systems
AI	Artificial Intelligence
AV	Automated Vehicle
BGT	Behavioral Game Theory
CNN	Convolutional Neural Network
DTA	Difference in Time to Arrival
eHMI	External Human-Machine Interface
FCW	Forward-Collision Warning
FOV	Field of View
GDPR	General Data Protection Regulations
IIHS	Insurance Institute for Highway Safety
LOOCV	Leave-One-Out Cross-Validation
NACTO	National Association of City Transportation Officials
ND	Naturalistic Driving
PET	Post-Encroachment Time
QRE	Quantal Response Equilibrium
SMOTE	Synthetic Minority Oversampling Technique
TTA	Time To Intersection
ΔTTA	Difference in Time To Intersection (estimation)
TT	Test Track
TAOI	Time to the Area Of Interest
VRU	Vulnerable Road User
VR	Virtual Reality

1 Introduction

1.1 Cyclists’ crashes with motorized vehicles

Cyclists face a higher likelihood of injury than motorists, both in total crashes and per distance travelled. In contrast to the share of driver fatalities, that of cyclist fatalities has been increasing in European countries in recent years [1]. Unlike road users in passenger cars, cyclists are not protected by a metal compartment, so they are highly susceptible to severe injury in crashes with motorized vehicles.

According to Hellman et al. (2016), over 70% of cyclists’ crashes occur where they share the path with motorized vehicles [2]. Unsignalized intersections are particularly problematic because users must come to an agreement in order to cross safely. In Sweden, priority rules dictate that cyclists usually have the right of way in this scenario; however, according to Svensson et al. (2010), in 42% of cases, drivers do not yield to cyclists [3].

1.2 Crash prevention methods for cyclists’ interactions with motorized vehicles

The most important countermeasures to prevent cyclists’ crashes with motorized vehicles are: 1) automated driving systems and vehicle safety systems, 2) infrastructure design, 3) education and policy making, and 4) consumer rating programs.

Automated driving systems and automated vehicles are being developed with the promise of removing human error in driving tasks. At higher levels of automation, all the driving tasks will be performed by the vehicle, including continuous decision-making in complex urban environments. The three main phases of automated driving functionality are sensing, prediction, and action [4]. The first phase is performed by the mounted sensors inside and outside the vehicle, which collect information about the surroundings. The second phase is based on the sensing data; the automated vehicle (AV) uses its prediction models and algorithms to decide how to proceed given the current situation. A substantial amount of research has been done on this phase [6, 7]. In the last phase, the vehicle acts on the decisions made in the second phase. For a successful implementation of AVs in urban areas, there is a need to define a safe and comfortable way of interacting with vulnerable road users (VRUs). Thus, it is important to investigate and extract cyclists’ behavioral patterns (from a variety of data sources) when they interact with motorized vehicles, in order to develop predictive models for AVs to safely interact with cyclists, especially at crossings where a missed interaction may have severe consequences.

Safety systems in today's vehicles are either active or passive. Active safety systems aim to prevent crashes, while passive safety systems aim to reduce crash consequences, such as injuries. Active safety systems are continuously looking for threats by predicting possible critical scenarios. Active safety systems are a subset of Advanced Driver Assistance Systems (ADAS) that improve road safety by detecting and responding to critical situations before they escalate into crashes. Examples include Automatic Emergency Braking (AEB) and Forward-Collision Warning (FCW). ADASs also encompass features like adaptive cruise control, lane-keeping assist, and traffic sign recognition—all relying on sensors (e.g., cameras, radar, LiDAR), control algorithms, and human-machine interfaces to monitor, alert, and intervene in real time. This integrated, technological approach helps reduce human error and improve immediate safety, while building the groundwork for the fully autonomous systems required for higher levels of vehicle automation [7][8]. Two examples of active safety systems commonly used in modern cars are forward-collision warning (FCW) and autonomous emergency braking (AEB). The former issues a warning to the driver in the event of an imminent crash with an object in front. In the case of bicycle-vehicle interactions at intersections, if drivers do not see the approaching cyclist, the FCW can warn them. The AEB first issues a warning; if the driver does not respond, the system can stop the vehicle to prevent a crash [9]. For successful deployment of active safety systems in urban environments, it is essential to establish methods that ensure safe and comfortable interactions with cyclists.

Many researchers have pointed out the importance of infrastructure design for cyclists' safety. For instance, Wegman et al. (2010) enumerate different infrastructure measures for reducing cyclists' crashes, including dedicated cycling paths and special design requirements for roundabouts [10]. Boda et al. (2018) conducted a study on the interaction between motorized vehicles and cyclists at an intersection; they found that the drivers' response process was mainly influenced by the visibility of the cyclist [11]. In another study, Jensen (2016) gives some insights about how to increase cyclists' safety through better design of intersections and roundabouts [12]. Although physically separating VRUs from motorized traffic can substantially reduce injuries and fatalities, implementing these improvements in many urban contexts can prove prohibitively expensive or otherwise impractical.

Policymakers try to reduce the risk of crashes by imposing laws or giving recommendations to regulate the movement of road users. For instance, in Sweden motorized vehicles should give priority to crossing cyclists who are riding in dedicated, marked cycling lanes; cyclists have a responsibility to pay attention to other road users when they approach unsignalized intersections as well. There are other ways to reduce the potential risks in encounters between cyclists and motorized vehicles. For example, some countries (e.g., Australia, New Zealand, Argentina, and Cyprus) have made helmets mandatory for cyclists [13]. In addition, some countries teach school children safe and reliable cycling techniques as part of their educational program, while others enforce regulations on alcohol impairment among cyclists, subjecting them to legal blood alcohol limits similar to those for motorists. [14].

Consumer rating programs, such as the European New Car Assessment Programme (Euro NCAP) and the Insurance Institute for Highway Safety (IIHS), significantly influence vehicle safety by establishing stringent protocols to evaluate both vehicle crashworthiness and ADAS effectiveness. With an increasing focus on VRUs, Euro NCAP has developed comprehensive test procedures that include cyclist collision scenarios in order to ensure that manufacturers develop robust detection and intervention technologies to address them [15].

A growing body of research reports the positive impact of these programs on real-world safety outcomes. Lie and Tingvall (2002) demonstrated a correlation between strong Euro NCAP performance and improved real-life injury outcomes, lending credibility to the program’s scoring system [16]. In the realm of ADASs, cyclist-specific AEB systems have shown particular effectiveness. Euro NCAP’s AEB VRU Test Protocol outlines multiple cyclist scenarios—both crossing and longitudinal—to replicate everyday traffic situations [15]. Recent naturalistic data suggests that properly implemented cyclist AEBs can significantly reduce the number and severity of vehicle-bicycle collisions [17].

Beyond the direct safety benefits of consumer rating programs, the heightened consumer awareness they promote plays a pivotal role in market uptake. Vehicles that achieve top safety ratings often enjoy a competitive sales advantage. As Euro NCAP and IIHS evolve their protocols—integrating insights from real-world crash data, behavioral research, and technological innovations, manufacturers are incentivized to develop more comprehensive safety solutions, benefiting all road users [18].

1.3 Behavioral models to improve safety

Predicting VRUs’ actions is crucial in order for AVs to achieve safe, trusted interactions with them in critical scenarios [6]. Similarly, the VRU may also have difficulty understanding the AV’s intention, due to a lack of explicit communication and the AV’s low speed [19]. VRU-AV interactions face particular challenges in mixed urban environments, like multiple interactions at a time or infrastructure design. [19]To overcome these challenges, researchers have proposed novel solutions, like using an external human-machine interface (eHMI) to communicate the AVs future actions [14, 15]. These interfaces are particularly efficient in low-speed urban situations where the VRUs have time to read the messages [22]. Proposed eHMI designs include a display on the vehicle, a projection on the road, and a light strip on the car [23]. However, it is the AV’s responsibility to correctly predict the VRUs’ intent during the interaction and safely react. While a great deal of research has been done on predicting pedestrians' intent during interactions with motorized vehicles [18, 19], only a small amount has focused on predicting cyclists' intent in urban spaces—and even less has tried to develop computational models that predict that intent. The focus of this thesis is to develop predictive models, and to investigate the factors affecting cyclists' yielding behavior at intersections and determine what visual cues are useful for predicting their intent in a specific interaction scenario.

Active safety systems utilize algorithms to detect a threat. In-time activation of these safety systems requires that the algorithms be well tuned, to avoid unnecessary interventions (when the driver was already aware of the threat). If the safety system repeatedly intervenes unnecessarily, the driver will no longer trust the system and stop using it. In this situation, the safety system cannot intervene when it is actually needed [26]. On the other hand, an active safety system's timely intervention can avoid the crash or mitigate its consequences, providing increased safety for all road users (including VRUs) [27]. Road users' behavioral models can improve threat assessment algorithms, so that they intervene earlier while remaining acceptable to the driver [27]. The main objective of using road user behavioral models in active safety systems is to avoid all crashes, including crashes with cyclists [28], and make sure that the driver trusts the system's performance. In a bicycle-vehicle interaction scenario in an intersection, the system should be able to predict the intent of the cyclist and react if needed.

Behavioral models can also inform infrastructure design and layout. For instance, knowing how visibility and intersection configuration affect cyclists' yielding behavior can help planners and engineers optimize road geometry, signage, and dedicated cycling paths to reduce conflicts and improve safety for all road users [10][11][12]. Road infrastructure can be tailored to encourage safer interactions when data-driven insights are integrated into crossing placements, roundabout configurations, and traffic-calming measures. When cyclists' typical responses to approaching vehicles are understood, design interventions—such as improved sight lines or more intuitive intersection layouts—can eliminate risky situations.

Moreover, these behavioral insights extend beyond vehicle automation and ADAS to influence education, policy-making, and even consumer protection assessments. For example, if research highlights the importance of clear communication in driver-cyclist encounters, policymakers can revise rules to mandate or promote clearer yield protocols, and educational curricula can present these interaction cues as a critical skill set [29]. In parallel, incorporating findings from cyclist behavior models into testing protocols—such as those from Euro NCAP—ensures that safety ratings reflect real-world challenges involving cyclists. This holistic approach, blending infrastructure optimization, targeted education, regulatory updates, and robust testing standards, fosters an environment where both human drivers and automated systems can better anticipate and accommodate cyclists' actions, ultimately leading to fewer collisions and more trusted interactions on the road.

1.4 Behavioral cues for predicting road users' behavior

Behavioral cues are critical for effectively implementing the methods mentioned in Section 1.2 (automated vehicles, infrastructure measures, education, and policy) because they provide early, observable indicators of a cyclist's likely actions. By decoding visual signals such as body position, head orientation, and speed, vehicles equipped with ADAS or AD functionality can anticipate cyclists' behavior and respond proactively to avoid potential conflicts. Similarly, these cues can be leveraged by infrastructure designers to optimize the layouts of intersections or bike lanes, making them more intuitive. Greater awareness of relevant behaviors can inform education and policy initiatives, ensuring that road users' intentions are more clearly communicated and understood. Thus, identifying and understanding these behavioral cues can lead to the development of robust, reliable predictive models that improve traffic safety in urban traffic.

Recent studies have shown that visual information about VRUs is important for predicting their decisions. For example, pedestrians' body position and head turn have been shown to relate to the decisions they make [23, 24]. A few studies have also found a connection between visual information about cyclists and their decision-making. For instance, Hemeren et al. (2014) showed videos of cyclists approaching an intersection to several participants and asked them which visual cues were more important for predicting whether the cyclists intended to go straight or turn left. They found that the cyclist's position (leaning or sitting up straight), head turn (toward their intended path), and speed were the most critical cues. In another study, Abadi et al. (2022) developed a neural network model to predict cyclists' intention to cross, using body and head orientation [32]. Thus, there is a need to extend this research by determining what visual cues are used by cyclists to communicate their decision to cross or yield to motorized vehicles at an intersection. Incorporating VRUs' visual information in predictive models may help AVs predict cyclists' intentions more accurately.

1.5 Interactions in traffic

Interactions among road users frequently happen when users share space in the traffic environment. As traffic volume increases, so does the number of conflicts and interactions. Markkula et al. (2020) defined interactions as situations in which the behavior of at least two road users is influenced by a space-sharing conflict [33]. Similarly, Thalya et al. (2020) defined an interaction as occurring when two or more road users share the road and try to communicate in order to probe the other's intent to navigate safely and comfortably [34].

A full description of a traffic interaction must also consider how each road user's decisions and actions influence the other road users. Behavioral models can provide a structured way to predict their actions, capturing the underlying cognitive and perceptual processes that guide drivers, cyclists, and pedestrians [35]. By incorporating communication cues (e.g., eye contact, gestures) and shared intentions from real-world interactions, behavioral models can demonstrate why conflicts occur and how they might be resolved [36]. Crashes can often be explained as communication failures, so ideally road users should be capable of robust communication and decision-making strategies. Integrating interaction concepts with behavioral modeling illustrates the complex decision-making mechanisms behind each road user's behavior, ultimately leading to the design of more effective traffic systems and safety interventions.

High-conflict interactions frequently occur where road users' paths intersect [37]; in fact, Hellman et al. (2016) found that over 70% of cyclists' crashes with motorized vehicles happen at crossings [2]. Crossings are either controlled by traffic signals or, in unsignalized intersections, by priority rules. The latter are usually more critical since they require communication and agreement between the road users to avoid conflict [37].

1.6 Behavioral models for cyclists' interactions with vehicles at intersections

To date, only a few studies have quantitatively investigated the interactions between cyclists and motorized vehicles at intersections. These studies used four types of data: naturalistic driving (ND), test track (TT), simulator, and video. ND data are considered to have the highest ecological validity [38]. The downsides of ND data are the confounders in the environment and the impossibility of repeating the scenarios. The second type of data, TT data, uses constructed scenarios, which are repeatable. The participants are not subject to real traffic, since they are driving on dedicated TTs, so the data are less ecologically valid compared to ND data. On the other hand, they still have real motion cues from the vehicles and the real environment around them, which makes TT data more ecologically valid than the third type, simulator data [39]. Simulators allow full control over the details of the tests and a safe environment to perform the scenarios. They are particularly useful for this thesis's subject (and any other research with a risk of collision between road users) because they remove the risk of collision between road users. In addition, like TT studies they offer repeatability while generally costing less than studies using TT and ND data. However, it should be noted that simulator data have the lowest ecological validity of all types of data [40]. Two types of simulators can be used for evaluating interactions between cyclists and motorized vehicles: driving simulators and riding simulators. The last type of data that has been used in these studies is video data. Participants are exposed to videos of a certain conflict scenario and are asked about their reaction to it. This type of data lacks accurate sensor information and has low ecological validity. On the other hand, like simulator and TT studies, videos offer repeatability and a safe testing environment.

One of the first works to investigate bicycle-vehicle interactions was written by Silvano et al. (2016) [41]. The authors used ND data from a roundabout to study the conflicts between cyclists and motorized vehicles [41]. They developed a two-stage framework for the interactions. In the first stage, their model determines whether a conflict is happening between the two road users; in the second stage, the driver's yielding behavior is modeled. The authors used binary logit models to determine the existence of a conflict and model the driver's yielding decision. They found that the relative time to arrival at the intersection, the vehicle's speed, and the cyclist's distance from the conflict zone are the significant variables affecting the driver's decision to yield. The limitations of this work are that they lacked complete trajectories of the involved road users, and they did not use any information about the cyclists in their modeling.

Boda et al. (2018) observed drivers' interactions with cyclists on a TT [11]. They used both a TT and a driving simulator to model and validate the driver's response to the approaching cyclist at an unsignalized intersection. The independent variables consisted of the cyclist's speed, the vehicle's speed, and the distance between them when they arrived at the intersection. They modeled the lateral clearance between the vehicle and the bike at the time the gas pedal was released and again at brake onset. They also modeled the brake onset behavior of each participant with respect to the changes in the independent variables. They concluded that the drivers' response behavior is mainly influenced by when the cyclist becomes visible at the intersection. In another work, Boda et al. (2020) developed a model for predicting driver behavior using two independent variables: optical looming control and projected post-encroachment time (PET) [42].

Simulators have been widely used to investigate cyclists' interactions with motorized vehicles; however, most of those works observed the drivers' behavior while overtaking cyclists—very few evaluated interactions at crossings. In one of the few, Bella and Silvestri (2018) used a driving simulator to test the effect of different countermeasures (consisting of infrastructure designs like raised islands and distinct pavement color) on drivers' responses when interacting with cyclists [40]. When the countermeasures were in place, the drivers had better braking profiles, in terms of smoother deceleration, compared to the baseline condition without countermeasures. The authors did not develop a predictive model for the interaction.

Another experiment, by Velasco et al. (2021), focused on cyclists' interactions with AVs and conventional vehicles. They showed videos of vehicles approaching an unsignalized intersection to participants wearing a virtual reality (VR) headset. The video was stopped at a critical moment, and participants (as cyclists) were asked if they would yield for the AV. The independent variables in this study consist of vehicle type (automated or conventional), gap size to intersection, vehicle speed, and who had the right of way. They found that the gap size and the right of way were the primary factors affecting the cyclists' decision whether to yield to the vehicles: the cyclists were less likely to yield if there were larger gap sizes and they had the right of way.

Despite the high frequency of cyclists' crashes with motorized vehicles at intersections, not much research has been done to quantitatively analyze their interactions with motorized vehicles. Further, parameters that may explain cyclist's behavior (like demographics) have not received much attention in the literature, partly because of the lack of datasets containing such information. Evaluating cyclists' behavior-related parameters may reveal different aspects of bicycle-vehicle interactions at unsignalized intersections.

At the present time, the main knowledge gap in bicycle-vehicle interactions is the lack of a detailed analysis of the cyclists' behavior. To be sure, a few studies have analyzed the interaction from the driver's point of view, determining how the driver responds to the presence of the cyclist [34, 33]. However, interaction models must be able to replicate cyclists' communications and behavioral patterns. We did not find any previous research that used computational models incorporating cyclists' information or behavioral cues. Further, no previous work has evaluated their predictive models using ND data from intersections. In fact, previous research on bicycle-vehicle interactions has only rarely used mathematical models to quantitatively analyze bicycle-vehicle interactions for application in active safety systems and AVs.

1.7 Aims and objectives

The main aim of this thesis is to contribute to safe interactions between AVs and cyclists by investigating the factors that affect the interactions and developing predictive models.

The following overall research objectives of the Ph.D. address the gaps identified in the previous research:

1. Investigating how cyclists and drivers manifest their intent when interacting with vehicles at unsignalized intersections.
2. Designing predictive models that combine kinematic data and behavioral cues (e.g., gaze, gestures, and pedaling) to predict cyclists' decisions at intersections.

3. Proposing behavioral models that AVs and ADAS may use to interact safely with cyclists at intersections.

To accomplish these objectives, we acquired data from: 1) a field data collection, 2) a riding simulator experiment, and 3) a driving simulator experiment. Using the field dataset, we analyzed naturalistic interactions between cyclists and motorized vehicles at an unsignalized intersection (Figure 1). This analysis provided valuable insights into how factors such as time-to-arrival differences, vehicle speed, cyclist kinematics, and non-verbal communication cues (e.g., gaze and gestures) influence interaction outcomes. These findings are crucial for understanding how cyclists manifest their intent while interacting with vehicles at unsignalized intersections (Objective 1) to develop predictive models that anticipate cyclists' yielding behavior and 2).

The riding simulator experiment extended this research by creating a controlled environment to study cyclists’ behavior under varying conditions, such as intersection visibility and the timing of the vehicle’s approach to the intersection. The results highlight the role of kinematic behaviors and visual attention in cyclists' decision-making processes, contributing to the refinement of predictive models (addressing Objectives 1 and 2).

The driving simulator experiment complemented these efforts by providing more information about drivers' behavior when interacting with cyclists. By incorporating gaze behavior, braking onset, and yielding decisions, this experiment offers insights into how AVs and ADAS can be designed to interact more safely with cyclists. The findings directly support Objective 3 by providing the foundation for developing behavioral models that simulate safe AV-cyclist interactions at unsignalized intersections. Together, the simulator experiments and the naturalistic observations contribute to addressing the research objectives and advancing safety in AV-cyclist interactions.

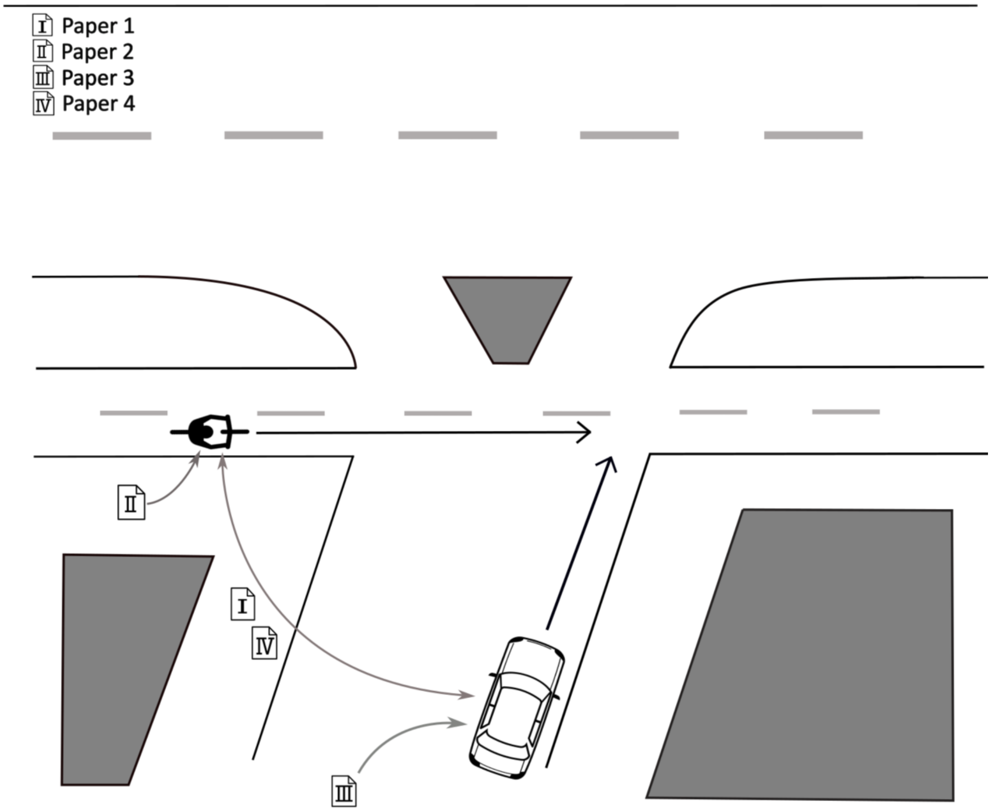

Figure 1- Overall picture of the PhD studies, showing the four papers. Papers 1 and 4 use ND data, Paper 2 uses data from the riding simulator study, and Paper 3 uses data from the driving simulator study.

2 Methodology

2.1 Bicycle-vehicle interactions: objective definition and assessment of crash risks

Interactions between motorized vehicles and cyclists occur in different forms, either in urban areas or on rural roads. In this thesis, a specific interaction scenario was investigated: it is one of the most common types of conflicts that leads to crashes in Sweden [2].

The scenario is an interaction at an unsignalized intersection between a motorized vehicle and a cyclist. The intersection is in Gothenburg (GPS coordinates: 57◦42′ 31.1″ N, 11◦56′ 22.9″ E). In 2016, there was a fatal crash between a student (cyclist) and a heavy truck at this intersection. The layout of the intersection and the moving direction of the involved road users is depicted inFigure 2: the cyclist approaches a three-way intersection and continues straight in a dedicated bike lane. The vehicle approaches the intersection from the cyclist's right side and turns right, cutting across the cyclists' path. The two road users need to negotiate who crosses first.

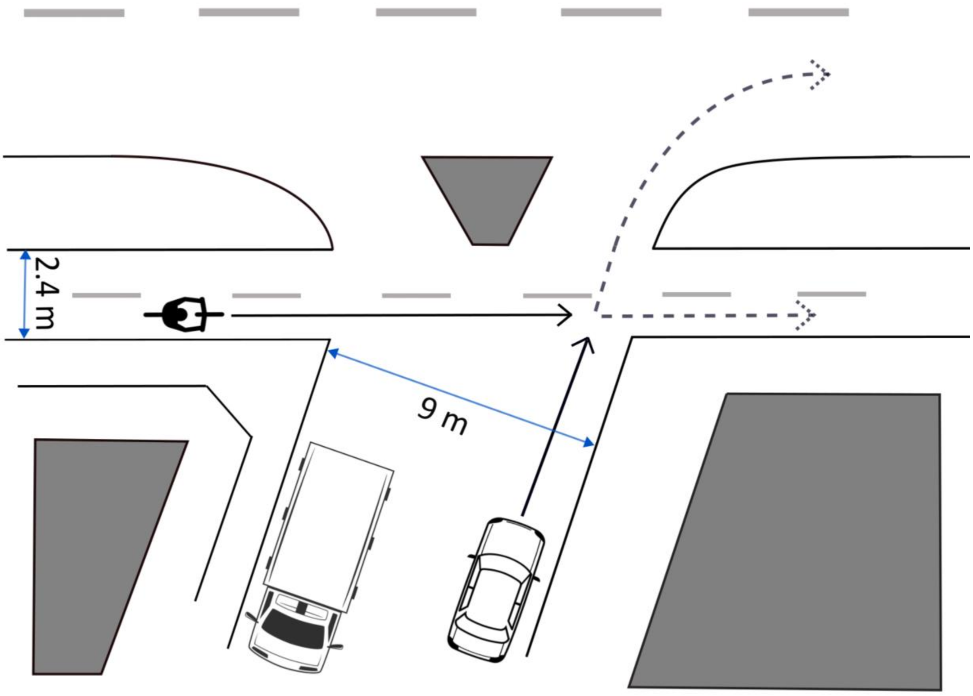

Figure 2- The intersection design and interaction scenario. The truck's position was manipulated to obstruct visibility to different degrees.

This thesis investigated how a variety of factors affected the interaction between the and the cyclist. These factors comprised kinematic parameters (like speeds and distances) and cyclists' visual information (like pedaling and head turn). Kinematic information has previously been used to model the behavior of drivers interacting with cyclists [42]; the factors that have been found to be important include cyclist speed, vehicle speed, and configuration of arrival (their relative distance) at the intersection [9, 33]. In this thesis, unsignalized intersection refers to any intersection lacking traffic signals, whether or not signs (stop or give way) are present.

Road users communicate with each other both explicitly and implicitly. Communication is explicit when it conveys a message deliberately (through gestures for example). Road users are always communicating implicitly, such as a driver's way of controlling speed while driving [35, 36].

2.2 Data sets

Different methodologies exist for data collection concerning the subject scenario in this thesis. These methods include ND data collection, field tests, TT experiments, and simulator experiments. Each data collection method has its inherent limitations and advantages. The main difference between the data types is the ecological validity; ND data has the highest ecological validity to investigate the road user's behavior. ND datasets are subject to issues like lower accuracy, higher data collection costs, and difficulties in finding interesting events. Due to the crash risk for the road users in the scenario in this thesis, field testing was not feasible. TTs also provide a realistic environment which can yield high-quality data for analysis. In addition, the controllability of TT tests is a great advantage for obtaining detailed aspects of driving behavior. However, the need for a lot of preparation to ensure that the TT resembles a real-world scenario is one of the disadvantages of this type of data. On the other hand, simulators are great tools for evaluating human behavior without subjecting participants to possible harm. Simulators also provide the chance to control the scenario and repeatedly test participants, for a lower cost than other data collection methods. The downside of simulator studies is that they have the lowest ecological validity of these four methodologies.

The idea of creating a "digital twin" of the real-world intersection played a critical role in the methodological strategy of this work. In essence, naturalistic data from a specific urban intersection in Gothenburg, Sweden, were first analyzed to identify the key variables (speed, visibility, and difference in time to arrival: DTA) most responsible for influencing driver-cyclist interactions in the real world. Within the controlled environment consisting of riding and driving simulators, key conditions within the digital intersection could be systematically manipulated, ensuring that the simulator experiments were as realistic as possible.

Another important dimension of this approach was the independent yet complementary investigation of drivers and cyclists. After establishing the interaction parameters and identifying critical events through ND data, the research team designed simulator studies that specifically examined the behavior of both road user types. First, the ND data provided a baseline representing drivers' and cyclists' real-world approaches to unsignalized intersections. The simulator experiments incorporated this knowledge and tested the impact of altering visibility conditions, vehicle approach timing, and other factors on cyclists' decision-making (in the riding simulator) and on drivers' yielding behavior (in the driving simulator). Thus, each study informed the next, ensuring that subsequent experiments were grounded in observed reality even as they explored scenarios that could not be tested on the road safely or within a reasonable budget. Notably, this thesis addresses adult cyclists only. Children may have distinct perceptual and cognitive responses while riding—an area that remains beyond our current scope but merits further investigation.

The data for PAPERs I and III were gathered at an urban intersection in Gothenburg, Sweden. VISCANDO, a company specializing in traffic surveillance systems, collected the data from an AI-based sensor positioned on a high-rise building corner, aimed at the focal point of potential conflicts. The sensor recorded the movements of both cyclists and motorized vehicles, allowing the extraction of interaction events between these road users. The accuracy of these events was verified by cross-referencing the corresponding videos. Kinematic parameters such as speed and distance were derived from the trajectory dataset and supplemented with information from cyclists' appearances on the videos. The videos were reduced according to GDPR (General Data Protection Regulations) regulations. Refer to Figure 3 for a visual representation of the intersection from the sensor's perspective.

Figure 3- Intersection from the mounted VISCANDO sensor.

We used ND data to analyze interactions involving both professional and non-professional drivers. In this context, “professional drivers” refers to those driving for occupational purposes—specifically truck and taxi drivers. While we grouped them together due to a limited sample size, we recognize that truck and taxi drivers may have distinct motivations or constraints that influence their yielding behavior.

The data for PAPER II were acquired through a riding simulator (see Figure 4). Participants wore a VR headset to observe the environment and were tasked with traversing an intersection (designed to closely resemble the one from the ND data). The experiment, evaluating the interaction shown in Figure 2, comprised 12 trials per participant. In this scenario, a cyclist rides straight in a bike lane, while a vehicle approaches from the right. Different sensors measured the cyclist’s activities during the test. Cyclists maintained a maximum speed of 18 km/hr, while the vehicle had an initial speed of 25 km/hr. The vehicle’s arrival was manipulated to meet the cyclist at various times; cyclists’ visibility conditions were also manipulated by changing the position of the truck. The analysis also incorporated participants’ questionnaire responses to provide additional insight into their behavior during the trials.

Figure 4- Bike simulator with VR headset

The data for PAPER IV were collected using a fixed-base driving simulator developed by Toyota Motors Europe (see Figure 5). Participants wore Tobii Pro 3 eye-tracking goggles. The intersection used in the simulation was a digital replica of a real-world location in Gothenburg, Sweden, designed to reflect realistic traffic conditions and cyclist interactions. The participants, all regular drivers, completed multiple trials in which they approached the intersection while a virtual cyclist entered from the left.

The two key independent variables in the study were intersection visibility (IV) and difference in time to arrival (DTA). The IV was manipulated by placing a truck at the corner of the intersection, which obstructed sightlines. Two different visibility distances were used in the experiment, 22 meters and 27 meters. These distances were measured from the point at which the cyclist first became visible to the driver to the center of the conflict zone. The DTA was the second key variable, which represented the temporal gap between the times that the cyclist and vehicle reached the intersection. The DTA was either 0.5 seconds, 1.0 seconds, or 1.5 seconds.

The data collected during the trials included vehicle speed, braking onset, and gaze metrics (including the time it took for participants to first fixate on the cyclist, the total number of fixations, and the duration of the first fixation). A total of eleven randomized trials were conducted for each participant, to account for any learning effects and reduce predictability. Participants also completed post-experiment questionnaires, which provided qualitative data about their experiences and perceptions during the simulations, as well as their thoughts on the realism of the interactions.

The data analysis involved using Bayesian regression models to explore the relationships between the key variables and the outcomes of interest: drivers' yielding decisions, braking patterns, and speed profiles. This methodology allowed the researchers to assess the effects of both kinematic factors (e.g., vehicle speed and DTA) and non-kinematic cues (e.g., gaze behavior) on driver decision-making.

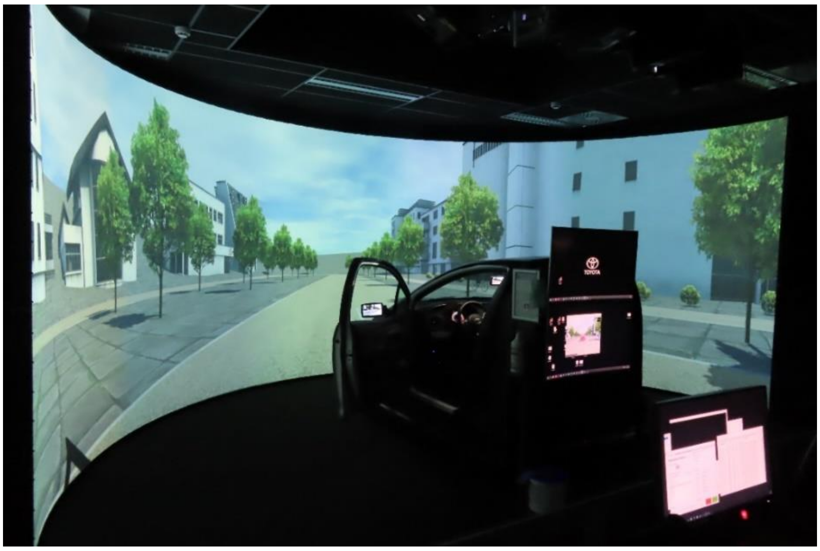

Figure 5- Driving simulator

2.3 Modeling techniques

We selected the modeling techniques (ranging from linear regression and logistic models to game-theoretic and Bayesian approaches) primarily because they allowed us to work effectively within the constraints of the available data while maintaining interpretability and flexibility. In contrast to many machine learning methods, which often require large, high-quality datasets and can be difficult to interpret, the frequentist, Bayesian, and game-theoretic frameworks are relatively data-efficient and provide transparent "open-box" insights into the relationships between variables. This transparency makes it easier to understand why certain factors are influential and how they interact, thereby ensuring that the models remain both accessible to domain experts and suitable for the methodological needs of our research. By pairing logistic regression for variable selection with BGT for modeling dynamic interactions, future hybrid models could retain interpretability while capturing the complexities of multi-actor decision-making. This integrated approach holds promise for more robust and nuanced predictions in complex traffic environments.

2.3.1 Linear regression models

Generalized linear regression models have been used for the analysis and modeling of the data in this thesis. Logit models are a form of linear regression model with a specific link function [45]; they model the probability of an event occurring based on a set of independent variables. The log odds of an event's occurrence are related to a linear combination of one or more independent variables [46]. The logit function transforms the linear predictors onto a probability scale from 0 to 1. In this paper, the cyclist's decision whether to cross the intersection before the vehicle was modeled as a binary outcome. Different independent variables were considered to test the model, including both road users' kinematics (speed and distance), and the cyclist's demographic and visual information. The general form of a logit model is as follows:

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

Where

P = the probability that a case is in one category

b_1, b_2, b_3 = vector of parameters to be estimated

x_1, x_2, x_3 = independent variables affecting the decision to yield

a = intercept

This thesis used the Python package *statsmodels* to obtain the model parameters. To balance the dataset based on the dependent variable, we used SMOTE (Synthetic Minority Oversampling Technique). To calculate the model prediction accuracy, the LOOCV (Leave One Out Cross-Validation) method was used.

Linear mixed-effect models are statistical tools used to analyze data with both fixed effects (general trends applicable to all data points) and random effects (variations specific to certain groups or subjects). Fixed effects capture the overall patterns or systematic influences that apply to the entire population under study. In contrast, random effects account for group-specific variations, acknowledging that different subgroups within the population may have unique characteristics [47]. These models are particularly useful when the experiment has repeated measures. Linear mixed-effect models are an extension of simple linear models that utilizes both fixed and random effects [48]. The logistic mixed-effect model, developed to predict the cyclists' yielding decision, has the general form expressed as in Equation 1, where P is the probability that a case is in one category, X the fixed-effect regressor matrix, β the vector of fixed effects, Z the random-effects regressor matrix, α the vector of random effects, and ε the observation error vector.

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

To estimate the model parameters, we used the R package *glmer*. The two main independent variables in the model consisted of the DTA and IV.

To model each cyclist's speed profile, we used an arctan function with four coefficients. The equation, which has three scaling factors and an offset factor, forms an s-shape which replicates the cyclist's speed during the approach to the intersection with respect to time. This model was used to compare the average cyclists' speed profiles across different trials. The following formula shows the general form of the equation:

$$Y = a * \arctan(\mathrm{b} * \mathrm{t} + \mathrm{c}) + d \tag{3}$$

The parameter fitting and evaluation were done using the MATLAB fitting function.

2.3.2 Game theoretic models

Game theoretic models are designed to analyze and predict the strategic interactions between "players," whose decisions impact one another's outcomes. In this thesis, game theoretic models were employed to model the interactions between cyclists and vehicles at unsignalized intersections. Two types of game theory were used: conventional game theory and behavioral game theory (BGT). The decision-making process during bicycle-vehicle interactions was analyzed, with a focus on kinematics factors [49].

Conventional Game Theory

Conventional game theory assumes that players act rationally and aim to maximize their payoffs based on complete information about the game structure. The decision-making process depends on each player's expectations about the other player's behavior. A Nash equilibrium is achieved when neither player has an incentive to unilaterally change strategy [50]. In this context, the cyclist and driver are the players, and their strategies are yielding or crossing the intersection first.

The structure of the conventional game theoretic model:

Players: Cyclists and vehicle drivers.

Strategies: Possible actions ("cross" or "yield").

Payoffs: Utilities or costs associated with each strategy combination, considering factors such as safety and time.

Information: Assumed to be perfect, meaning both players are fully aware of the payoffs and strategies.

The model predicts the outcomes of interactions by calculating the payoffs for each combination of strategies and identifying the equilibrium point where both players' decisions are stable.

Behavioral Game Theory

Behavioral game theory extends regular game theory by incorporating elements of bounded rationality, uncertainty, and cognitive biases [51]. In real-world scenarios, players do not always act perfectly rationally or have complete information. Behavioral game theory accounts for:

Probabilistic Decision-Making: Players select strategies with probabilities rather than deterministically choosing the optimal one.

Social Preferences: Decisions may reflect considerations such as fairness and social norms.

Quantal Response Equilibrium (QRE): A model in which the likelihood of choosing a strategy increases with its payoff but remains probabilistic due to randomness or uncertainty.

The BGT models used in this thesis were designed to better reflect real-world interactions, where cyclists and drivers might make suboptimal decisions due to limited information, misjudgments, or other human factors [52].

Model Implementation

The interaction between cyclists and vehicles was modeled as a two-player non-cooperative game. The cyclist's decision to cross or yield and the driver's decision to proceed or yield were modeled as binary strategies. The payoffs were calculated based on the following variables:

Kinematics: Vehicle and cyclist speeds, distances, and the DTA at the intersection.

For the conventional game theory model, the equilibrium solutions were computed based on deterministic strategies. For the BGT model, QRE was applied to estimate the probability distribution over strategies.

Mathematical Formulation

The payoff matrix for a simple game can be expressed as:

$$U_c = f(V, DTA) \quad (4)$$

$$U_d = f(V, DTA) \quad (5)$$

Where:

U_c and U_d: Payoffs for the cyclist and driver, respectively.

V: Vehicle and cyclist speeds.

DTA: Temporal gap between the cyclist and vehicle at the intersection.

The BGT model applies a probabilistic function to the payoffs:

$$P_i(S_i) = \frac{\exp(\lambda U_i(S_i))}{\Sigma_i \exp(\lambda U_i(S_i))} \quad (6)$$

Where:

$P_i(S_i)$: Probability of player i choosing strategy S_i.

$U_i(S_i)$: Payoff for player i under strategy S_i.

λ: Sensitivity parameter representing the player's degree of rationality.

Parameter Estimation and Validation

The parameters of the game theoretic models were estimated using naturalistic interaction data collected at unsignalized intersection. Observations included cyclist and vehicle trajectories, speeds, and behaviors. Logistic regression and QRE were implemented using Python and R to analyze the outcomes and fit the models to the data. Model performance was evaluated based on prediction accuracy and goodness-of-fit metrics.

2.3.3 Bayesian models

Bayesian modeling offers a powerful framework for statistical inference by integrating prior knowledge with observed data to update beliefs [53]. One of the sophisticated techniques within Bayesian statistics is mixed-effect Bayesian regression, also known as hierarchical Bayesian modeling. This technique is particularly advantageous for handling complex data structures involving multiple levels of variability.

Concept and Structure

Mixed-effect Bayesian regression models include both fixed and random effects, allowing data that exhibit hierarchical or nested structures to be analyzed.

The general form of a mixed-effect Bayesian regression model can be expressed as:

$$y_{ij} = \beta_0 + \beta_1 X_{ij} + u_j + \epsilon_{ij} \qquad (7)$$

Where:

y_{ij} represents the response variable for the i-th observation in the j-th group.

β_0 and β_1 are the fixed-effect coefficients.

X_{ij} is the predictor variable.

u_j denotes the random effect associated with the j-th group, typically assumed to follow a normal distribution with mean zero and variance

$$u_j \sim N(0, \sigma_u^2) \qquad (8)$$

ϵ_{ij} is the residual error term, assumed to follow a normal distribution with mean zero and variance σ^2.

Application in Traffic Safety Research

In the context of traffic safety research (as in this specific application, modeling yielding behavior at unsignalized intersections), mixed-effect Bayesian regression can effectively handle the variability among different drivers. For instance, fixed effects could include factors like vehicle speed and DTA, which influence yielding behavior uniformly across all drivers. Random effects could capture the variability specific to individual drivers, recognizing that each driver might exhibit unique yielding patterns.

Bayesian Framework

The Bayesian approach specifies prior distributions for both the fixed and random effects. These priors represent the initial beliefs about the parameters before the data are considered [54]. The observed data are then used to update these priors through Bayes' theorem, resulting in posterior distributions that reflect the updated beliefs.

The hierarchical structure of mixed-effect Bayesian models is particularly advantageous for:

1. Flexibility: These models can incorporate complex data structures and multiple levels.
2. Prior Knowledge: Bayesian methods allow the incorporation of prior knowledge or expert opinion, which can be particularly useful when data are sparse or when previous studies provide valuable insights.
3. Robustness: Bayesian models are robust to missing data and can provide probabilistic interpretations of model parameters values.
4. Inference in Random Effects: The hierarchical nature allows for detailed inference in both fixed and random effects, providing a comprehensive understanding of the variability in the data.

Methodological Implementation

The mixed-effect Bayesian regression model was implemented using the Stan probabilistic programming language, which facilitates efficient Bayesian inference through Markov Chain Monte Carlo (MCMC) sampling [55]. The model included prior distributions for all parameters, reflecting reasonable assumptions based on previous studies and domain expertise. The posterior distributions obtained from the model provided insights into the factors influencing drivers' yielding behavior, accounting for both fixed effects (e.g., vehicle speed, DTA) and random effects (e.g., individual driver differences).

3 Summary of papers

The results of this thesis are presented in the four appended papers. The following section provides a summary.

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

Background

Very little research has been done to quantitatively analyze and model the interaction between cyclists and motorized vehicles at intersections, although a large proportion of cyclists' crashes occur at intersections where they share the path with motorized vehicles. Accurate predictive models are needed to define a safe and comfortable way for AVs to interact safely with cyclists in this conflict scenario.

Aim

This paper aims to provide insights into cyclist-motorized vehicle interactions based on ND data. The interaction events were used to investigate the factors influencing cyclists' yielding behavior.

Methods

The ND data for this experiment were acquired from an unsignalized intersection in Gothenburg, Sweden. Fourteen days' worth of observations were searched to find relevant interaction events between cyclists and motorized vehicles. Relevant events were defined as those with a DTA within a certain range. A total of 105 interaction events were extracted from the trajectory dataset; more information about them was added later by checking the corresponding sensory data. For each interaction event, kinematics (both road users' speeds and distances), cyclists' visual information (head turn and pedaling), and observed demographics were collected. Safety metrics like PET were also measured to determine the criticality of the scenario. Logistic regression was used to quantify the effect of different parameters on the cyclist's decision to cross.

Results

Modeling results showed that both kinematics (road users' speeds and DTA) and cyclists' visual information (head turn and pedaling) are significant predictors for cyclists' decision whether to cross first. The Leave One Out Cross-Validation (LOOCV) method showed an acceptable model accuracy of 83%.

Conclusions

It was found that while both the kinematics and the cyclists' visual information are useful for predicting whether cyclists will cross ahead of an oncoming vehicle, kinematics play a more important role. The findings of this study may be used in AV algorithms, which could supplement cyclists' kinematics with their visual information to improve the probability of correctly predicting whether they will yield.

3.2 PAPER II: Understanding the interaction between cyclists and automated vehicles at unsignalized intersections: Results from a cycling simulator study

Background

While other road users are experiencing fewer fatalities, cyclist fatalities have been increasing in recent years in Europe. Although most cyclist crashes occur at crossings, there is not much research analyzing the conflicts between cyclists and motorized vehicles. Understanding cyclists' behavioral patterns will help researchers develop accurate predictive models, which will help AVs interact safely and comfortably with cyclists in conflict scenarios.

Aim

This paper aims to provide a descriptive statistical model of cyclists' behavior when interacting with AVs at unsignalized intersections, by extracting cyclists' behavioral patterns during the interaction.

Methods

A bike simulator was used to collect data from participants riding through an intersection similar to the one where the ND data were collected. Twenty-seven participants were instructed to pass through the intersection several times. The participants experienced the environment by means of a VR headset. A car was shown approaching the intersection from the their right, and the participants needed to decide what to do. The effects of the DTA and the IV on the cyclists' response process were investigated. Participants filled out a questionnaire after the experiment to record their experience during the interaction scenario. Data from the simulator's sensors and the questionnaire were used to determine how the cyclists interacted with the AVs and what factors influenced their decision-making, respectively. A mixed-effect logistic regression model was used to determine the effects of the independent variables on cyclists' decisions whether to cross the intersection first. Cyclists' speed profiles were modeled using an arctan function to compare the average profiles across different trials.

Results

Data from 25 participants were analyzed. As they approached the intersection, most cyclists followed a consistent sequence of actions that was influenced by changes in the independent variables. Among the independent variables that were tested in the model, only the DTA affected the cyclists' decision to cross the intersection first. The earlier the cyclists arrived at the intersection relative to the car (greater DTA), the more likely they were to cross the intersection first. When cyclists' average speed profiles were compared, the results showed that the greater the FOV distance, the sooner the cyclists noticed the vehicle—as indicated by a smoother, more gradual deceleration rate. In the questionnaires, participants mentioned that the lack of communication and eye contact (due to the lack of an actual driver) made them ride more cautiously.

Conclusions

The DTA was shown to have the most influence on the cyclists' behavior. On the other hand, their behavior was also affected by the fact that the vehicle was driverless, which caused them to act more conservatively. Incorporating surrogate methods for communication with AVs may facilitate their acceptance by cyclists in the future. Furthermore, earlier visibility benefited the cyclists, who then adapted their speed earlier and demonstrated smoother speed profiles. This finding holds significance for intersection design, since the importance of visibility to mitigate the severity of conflicts is confirmed.

3.3 PAPER III: Modelling vehicle-cyclists’ interactions to support automated driving and advanced driving assistance systems

Background

Unsignalized intersections are frequently cited as high-risk areas for collisions between cyclists and motorized vehicles, primarily due to unclear priority rules and variability in driver behavior. The advent of AVs presents an opportunity to enhance cyclist safety by leveraging predictive models that account for cyclist yielding behaviors. However, limited research has been done to explore the dynamics of interaction between drivers and cyclists at unsignalized intersections. A deeper understanding of these interactions could inform the development of advanced predictive algorithms, enabling ADAS and AVs to navigate these conflict-prone scenarios more safely and effectively than human drivers.

Aim

This paper aims to investigate how drivers and cyclists interact at unsignalized intersections, focusing on the role of intersection visibility (IV), difference in time to arrival (DTA), and gaze behavior in shaping drivers' yielding decisions, braking patterns, and speed profiles. The study uses driving simulation and eye-tracking technology to identify key variables that influence these interactions and their implications for infrastructure and AV systems.

Methods

The study utilized a fixed-base driving simulator combined with Tobii Pro 2 eye-tracking goggles to simulate interactions at an unsignalized intersection. The simulated intersection was a digital replica of an intersection in Gothenburg, Sweden. Independent variables included IV, manipulated through the placement of a truck to obstruct sightlines, and DTA, defined as the temporal gap between the vehicle and cyclist arriving at the intersection. Participants completed multiple trials under various configurations of IV and DTA. Data on vehicle speed, braking behavior, and gaze metrics were collected. Bayesian regression models were used to analyze the effects of these variables on drivers' yielding decisions, braking onset, and speed profiles.

Results

This study examined driver-cyclist interactions at unsignalized intersections using a driving simulator equipped with eye-tracking technology. The analysis revealed that intersection visibility (IV) and difference in time to arrival (DTA) were key determinants of drivers' yielding behavior. Increased visibility distances allowed drivers to detect and respond to cyclists earlier, significantly increasing the likelihood of yielding. Similarly, shorter DTAs, where cyclists and vehicles arrived at the intersection closer in time, prompted drivers to yield more frequently. Gaze behavior also emerged as a critical factor, with earlier fixation on the cyclist correlating with a higher probability of yielding, underscoring the role of attentiveness and hazard recognition in decision-making processes.

While the braking distance model did not identify statistically significant predictors, variables such as DTA, vehicle speed, and gaze metrics were close to significance thresholds, suggesting a complex interplay of factors influencing braking behavior. The modeling of speed profiles demonstrated that drivers adjusted their deceleration patterns based on IV and DTA, with limited visibility or shorter arrival times resulting in more cautious behaviors. These findings were complemented by subjective feedback from participants, which emphasized the lack of communication cues and eye contact with the cyclist in the simulator, potentially impacting the realism of the interactions.

Conclusions

This study underscores the importance of kinematic factors (e.g., IV, DTA) and non-kinematic factors (e.g., gaze behavior) in shaping driver-cyclist interactions at unsignalized intersections. From an infrastructure design perspective, enhancing visibility through measures can significantly reduce conflicts and improve safety. For AVs, the study identifies critical variables that should be integrated into predictive models to improve their ability to anticipate cyclist behavior. Specifically, gaze metrics and kinematic data can enhance ADAS and AVs' threat assessment and decision-making capabilities, enabling safer interactions.

In summary, this research highlights actionable opportunities for both infrastructure improvement and the development of ADAS and AVs. By incorporating these findings into real-world designs and AV algorithms, can create safer and more efficient intersections. Future work should validate these insights in naturalistic settings and explore their applicability across diverse intersection configurations and traffic conditions.

3.4 PAPER IV: Cyclists interactions with professional and non-professional drivers: Observations and game theoretic models

Background

According to crash data reports, most collisions between cyclists and motorized vehicles occur at unsignalized intersections where vehicle priority is not regulated by traffic lights. In the era of automated driving, ensuring the safety of cyclists at these intersections is crucial. AVs need predictive models that describe how cyclists cross and yield at intersections to interact safely with them. Previous studies have modeled bicycle-vehicle interactions but have not addressed professional and non-professional specifically.

Aim

This paper aims to compare the interactions between cyclists and both professional and non-professional drivers at unsignalized intersections. The study developed logit and behavioral game theoretic (BGT) models using naturalistic data to understand and predict the outcomes of these interactions.

Methods

Naturalistic data were collected at an unsignalized intersection in Gothenburg, Sweden, using stereovision and AI-based sensors. Over 14 days, data on trajectories, speeds, and headings of road users were recorded at 20 Hz. Interaction events between a single vehicle and a single cyclist were identified based on the difference in time to arrival (DTA) at the intersection. A total of 156 interaction events were analyzed. Logistic regression and BGT models were used to quantify the effects of different variables on the interaction outcome.

Results

Modeling results indicated that both kinematic factors (vehicle and cyclist speeds, DTA) and non-kinematic cues (head turn, pedaling) significantly influence cyclists' decisions to cross first. Professional drivers were found to yield to cyclists less often than non-professional drivers. BGT models outperformed logit models in predicting interaction outcomes, showing higher accuracy.

Conclusions

The study found that professional drivers are less likely to yield to cyclists than non-professional drivers, highlighting the need for AVs and ADAS to account for driver type in their predictive models. Both kinematic and behavioral cues are valuable for predicting cyclists' behaviors, with kinematics playing a more significant role. The findings suggest that incorporating these models into AV and ADAS may enhance the safety and predictability of their interactions with cyclists.

4 Discussion

This discussion synthesizes the findings from the multiple studies presented in this thesis, highlighting how the interplay between kinematic factors, cyclists' visual cues, and infrastructural conditions at unsignalized intersections affect the interaction between cyclists and AVs. Drawing on both naturalistic and simulator data, the work illustrates the importance of critical parameters like DTA, speed, and visibility in determining who proceeds first and how smoothly these interactions unfold. In considering factors ranging from explicit and implicit communication to driver type and intersection design, the discussion identifies opportunities for enhancing traffic safety through informed improvements in vehicle algorithms, infrastructure planning, and policy interventions.

Conflicts between motorized vehicles and cyclists commonly occur at crossings. The studied intersection is unsignalized and governed by priority rules. According to Swedish traffic rules, the vehicle should give priority to the cyclist at this intersection (which has a dedicated cycling path), while cyclists should be aware of their surroundings and pass through the intersection carefully. However, in practice, motorized vehicles do not always give priority to cyclists, and both road users need to negotiate who crosses the intersection first. Understanding the factors affecting their interactions is essential for improving safety in a reality where priority rules alone cannot be trusted.

4.1 Cyclists' interactions with motorized vehicles: influencing factors and behavioral patterns

The present thesis investigated one of the most common types of interaction scenarios between bicycles and vehicles, specifically when both the vehicle and the cyclist continue straight [56]. Different parameters can influence the outcome, including aspects of infrastructure design, road users' kinematics, demographics, and road users' characteristics. The three studies conducted in this thesis were intended to capture the effect of different variables on the outcome of the 'vehicle going straight versus cyclist going straight' interaction. The finding that the variables affecting the outcome the most are DTA and visibility confirms the results of previous studies [9, 33]. We may hypothesize that the significant variables in these three studies are the most important parameters affecting bicycle-vehicle interaction. However, this conclusion needs to be confirmed by analyzing data from different locations.

Kinematics factors

Kinematics play a major role in the interactions between cyclists and motorized vehicles, as is evident from both previous results and those from this thesis [33, 42]. The developed logistic model in PAPER I uses three kinematic variables:

cyclist speed, vehicle speed, and DTA. It is worth pointing out that the effect sizes of the kinematic variables in this paper were larger than the effect sizes of the variables related to the cyclists' visual information. Therefore, we can predict cyclists' decision-making relying on kinematics alone, but the prediction can be further improved by considering cyclists' visual information.

Kinematic variables were also identified as significant predictors in subsequent simulator studies. PAPER II sought to investigate how both kinematic and visual information from cyclists could enhance the prediction of who would cross first. The DTA was shown to significantly influence cyclists' decisions to cross the intersection first. Moreover, the results support the notion that cyclists' behavioral cues—such as whether they kept pedaling or turned their head toward the approaching vehicle—could further refine predictive accuracy. In PAPER III, a Bayesian logistic regression model revealed that vehicle speed and DTA are significant kinematic predictors. The paper also introduced the critical role of visibility. Greater visibility gave road users more time to recognize one another, facilitating earlier adjustments in speed and smoother deceleration rates. These results complement the insights from PAPER II, which demonstrated that extended visibility led to less severe interactions and more gradual deceleration profiles. By corroborating earlier findings about the importance of visibility from studies conducted by Bella & Silvestri (2018) and Boda et al. (2018), PAPER III provided stronger evidence that enhancing visibility at intersections can lead to safer and more comfortable outcomes for both cyclists and drivers [40][11]. In essence, PAPER III combined the core significance of the kinematics established in PAPERs I and II with a new emphasis on infrastructural variables, to form a more comprehensive understanding of road user behavior in this scenario.

PAPER IV went a step further by examining how differences in driver type affect bicycle-vehicle interactions, as well as how advanced behavioral models can capture these dynamics. The paper demonstrated that the BGT model could reliably predict interaction outcomes using only ΔDTA, further emphasizing the critical role of kinematics in driver-cyclist interactions. The findings indicated that professional drivers (truck and taxi drivers) have a riskier behavior profile, since they are less inclined to yield to cyclists than non-professional drivers (passenger car drivers). This outcome provides critical insights into how driver type shapes the negotiation process at intersections, influencing who crosses first.

Explicit and implicit communication

Road users use both implicit and explicit communication strategies to proceed in traffic and interact with other road users. Current AD functions mostly predict the future state of other road users by their kinematics. However, recent research has shown the potential of using cyclists' visual information in predicting their intent in traffic [23, 37, 25, 43]. Abadi et al. (2022) proposed a neural network model using body position and head orientation to estimate the cyclist's crossing intention [32]. In another study, Hemeren et al. (2014) found that cyclists' position, head turn, and speed are the most critical visual cues for predicting their future path [58]. Grigoropoulos et al. (2022) devised a predictive model that relies only on cyclists' visual information to predict their direction of movement at an intersection [59]. They achieved an acceptable level of accuracy at predicting cyclists' intent at an intersection, establishing the importance of cyclists' visual information in predictive models.

In PAPERs I and II in this thesis, we also found that cyclists' visual information is relevant for predicting their yielding decision. For instance, our results confirm the previous findings that head turn is an important signal for crossing decisions. While the primary focus of Grigoropoulos et al. (2022) and Hemeren et al. (2014) was the utilization of cyclists' visual cues to anticipate their travel direction at intersections, their research underscores the crucial role that cyclists' visual information plays in accurately predicting their decision-making process. PAPER I reports that cyclists' pedaling and head turn were significant for predicting who will cross the intersection first—as expected, if cyclists keep pedaling, it is more probable that they are going to cross the intersection before the vehicle. Moreover, it is more likely that a cyclist who turns toward the approaching vehicle will cross the intersection first. In PAPER II, the simulator data showed that participants had a consistent sequence of actions as they cycled toward the intersection. Knowing cyclists' behavioral patterns will help predict when they brake or stop pedaling during the interaction. Our studies show that adding extra information from visual cues to the predictive algorithms may lead them to make more accurate predictions of cyclists' behavior, helping improve the safety and comfort of interactions between cyclists and AVs. However, in the driving simulator experiment, it was not possible to manipulate cyclists' behavioral cues (such as head movements and pedaling) within the experimental setup, so it was not possible to assess their impact on interaction outcomes. As a result, the predictive models were developed using only kinematic factors, driver characteristics, and gaze information.

Glance behavior

Glance behavior—captured via eye-tracking systems, head pose estimation, or camera-based monitoring—plays a pivotal role in understanding and predicting drivers' intentions and overall risk profiles. In this thesis, the eye-tracking system employed in the driving simulator experiment provided valuable insights into how glance metrics can anticipate a driver's response to upcoming threats. The results indicated that time to the area of interest (TAOI) significantly influences decisions to yield to an approaching cyclist, underscoring the importance of driver attention and visual scanning for safe maneuvers at conflict points. Consequently, integrating glance-based metrics—such as TAOI—into ADASs could enhance their ability to predict and respond to drivers' behaviors in real-world scenarios. Similarly, Doshi and Trivedi (2009) demonstrated that incorporating gaze-based features into on-road prediction models improves the accuracy of forecasting maneuvers such as lane changes and turns [60]. Fan et al. (2019) further showed how deep learning algorithms integrating eye-gaze data with driving performance and environmental cues can enhance real-time driver behavior predictions [61]. These findings underscore the finding that monitoring drivers' focal points and scanning patterns enables a more precise assessment of their situational awareness and decision-making. Consequently, such gaze-based indicators can be integrated into ADAS to refine risk predictions, inform proactive vehicle responses, and ultimately support safer navigation in complex traffic scenarios.

Infrastructure

In PAPERs II and III, we observed the effect of visibility on the cyclists' and drivers' response processes at an unsignalized intersection. In PAPER II, it was reported that when more road is visible to the cyclists and they can spot other road users earlier, they have more time to adopt an appropriate strategy—for an overall safer interaction. With extended visibility, the cyclists had smoother speed profiles because they decelerated more gradually, validating the findings of Bella & Silvestri (2018) regarding cyclists' earlier speed adjustment when visibility was extended. This finding also corroborates the research conducted by Boda et al. (2018) concerning the interplay between cyclists and motorized vehicles, underscoring the significance of visibility. A similar outcome was observed in the driving simulator experiment (PAPER III), which revealed that visibility significantly influences drivers' yielding decisions: drivers who spotted cyclists earlier were more likely to yield. Additionally, earlier visibility allowed drivers more time to adjust their speed in response to the approaching cyclist, enabling a broader range of speed adaptations.

The National Association of City Transportation Officials (NACTO) recommends that intersection design should facilitate eye contact between street users, ensuring that VRUs intuitively read intersections as shared spaces [62]. The organization suggests that visibility can be achieved through a variety of design strategies, including intersection "daylighting," low-speed intersection approaches, trimmed vegetation, and stopping sight distances. Gonzalez-Gomez et al. (2022) state that visibility is one of the four key factors affecting roundabout safety [63]. The other three are: approaching drivers, comprehensibility of traffic operations, and adequate space for the largest permitted vehicles.

Given the significance of visibility (highlighted in this study and prior research), urban planners have reason to leverage these findings to craft intersections that prioritize sufficient visibility, thus improving the safety of cyclists as well as other road users, particularly VRUs. Furthermore, AV developers can apply this knowledge to enhance the design of their systems, so that AVs exhibit more cautious behavior in intersections characterized by restricted visibility.

4.2 Differences in data types: challenges and opportunities

Two different types of data (ND and simulator) were used in this thesis for analysis and modeling; each has its own strengths and weaknesses. In the first study (PAPERs I and IV), ND data was used to evaluate the interaction events. This type of dataset has the highest possible ecological validity and offers the possibility to observe road users' behavior [39]. However, the number of events that could be used in this thesis was limited due to the limitations in data collection and resources. As a matter of fact, unlike simulator data, ND data are subject to many confounding factors that may influence the interaction. To reduce the effects of extraneous factors, an effort was made in this thesis to extract clean interaction events from the ND dataset (with minimal influence from other road users). A second difference between them is that the simulator data measurements were more accurate than the ND data. The ND data were provided by a single sensor attached to a building, and as the distance from the sensor increased, the measurement accuracy decreased. In contrast, the simulator provided highly accurate data on different aspects of cyclists' behavior, like pedaling and braking. There was also a difference in the availability of participants' demographic information, which can be crucial for understanding variations in behavior across different groups: it was only available in the simulator environments [64]. Obtaining demographic details in naturalistic settings poses challenges and is often impossible or unfeasible, further underscoring the complementary nature of both data types.

Simulators, as utilized in PAPERs II and III, offer a more controlled environment compared to naturalistic driving (ND) datasets. The ability to collect data repeatedly under identical scenarios ensures a higher volume of relevant data for specific situations. In addition, simulators are invaluable for studying human behavior in complex and potentially hazardous scenarios, like those examined in this thesis, without exposing participants to any risk [65]. However, the ecological validity of simulator environments must be assessed in a separate study to ensure their relevance to real-world conditions [66]. While data collection in simulators is more straightforward than in ND datasets, considerable time and effort must be invested in designing and preparing realistic scenarios within the simulation environment.

In spite of these differences, trends in the important factors that affected the interaction events were similar for both types of data. For instance, the DTA variable influenced the interaction outcome in similar ways in all three datasets. However, the distributions of coefficients varied in these datasets; the variety of influencing factors was higher in the ND dataset. This overall difference can be attributed to differences in measurements, individual cyclist participants, and the environment for the three datasets. In addition, factors like the presence of other road users may have influenced the interactions in the ND dataset. Obtaining the same trends using three datasets with intrinsic differences contributes to the validity of the results.

4.3 Implications for traffic safety

4.3.1 Incorporating cyclists' visual information into AV predictive algorithms

The timely, accurate predictions made in this thesis about cyclists' behavior can be used to improve the algorithms of automated driving systems, leading to safer and more comfortable performance in future traffic. The model developed in PAPER I is only the first step in the use of visual information to predict cyclists' intent during interactions with AVs. The systems can obtain both kinematics and visual information from their on-board sensors to predict cyclists' behavior in conflicting scenarios. Recent work on how to extract cyclists' visual information from video data can facilitate the acquisition of this kind of information from in-vehicle sensors [32]. Providing cyclists' visual information for predictive algorithms would enable safer, more comfortable interactions between AVs and cyclists at unsignalized intersections (and, potentially, elsewhere), as well as increasing trust in AVs. Clearly, a series of integrated steps, based on the assumption that AVs should behave like "good" human drivers in mixed traffic environments [67], is still required to optimize cyclist safety. Now that a preliminary model is available, as a next step AVs need reliable sensor systems and computer vision methods to capture and interpret subtle cues—such as a cyclist's head turns or pedaling behavior—under a variety of conditions [68][32]. This information must subsequently be integrated into predictive models that combine kinematic data with visual signals to accurately anticipate cyclists' intentions and trajectories [58][59]. Finally, the AVs must be programmed to respond cautiously and cooperatively, mirroring the courteous and law-abiding behavior of "good" human drivers: yielding when required, adjusting speed smoothly, and maintaining clear, understandable movements that reassure cyclists and other VRUs. Human-like, safety-first behavior is widely regarded as essential for fostering trust in automated systems [69]. By meeting these conditions, AVs can create safer and more comfortable interactions, ultimately encouraging greater public confidence and acceptance of automated transportation technologies.

4.3.2 Influence of driver type on cyclist safety

One finding in PAPER IV underscore differences between professional and non-professional drivers' interactions with cyclists at unsignalized intersections. Taxi and truck drivers yielded less often than non-professional drivers, perhaps due to experience, habitual risk-taking, economic pressures, or driving styles ([70][71][72][73]). This was reflected in the BGT model outputs, which indicated that professional drivers were more likely to cross the intersection first than non-professional drivers under the same ΔTTA conditions. Professional drivers exhibited higher approach speeds than non-professional drivers. This disparity can affect cyclists' comfort and safety, particularly if they expect all drivers to exhibit the same yielding behavior. The issue could be addressed with targeted policies for professional drivers that enhance training, emphasize safer driving behaviors, and foster an understanding of the vulnerabilities of cyclists. Now that it appears that professional drivers often approach intersections more aggressively, AV algorithms can adapt their driving strategies to account for the expected behavior of taxi and truck drivers. The adaptations might include anticipating non-yielding maneuvers earlier, adjusting approach speeds, and maintaining a safer distance—to minimize conflicts and ensure a higher level of safety for all road users (PAPER IV).

4.3.3 Modeling approaches for improved predictions

Combining kinematic and non-kinematic factors in predictive models substantially increases the accuracy of predicting interaction outcomes (Papers I and IV). Early work employed logistic (logit) regression to highlight key predictors such as time-to-arrival (TTA) for both cyclists and vehicles, cyclist distance, and non-kinematic cues. The subsequent introduction of BGT models further enhanced both robustness and precision (Paper IV), outperforming simpler statistical methods in capturing the complexity and non-linearity of human decision-making [52]. For AVs, these advanced models—together with sensors and algorithms capable of detecting both kinematic and visual cues—offer a promising approach to safer, more intuitive vehicle-cyclist interactions.

Incorporating these models into AD and ADAS stands to greatly improve safety and interaction quality in mixed traffic. For instance, computer vision algorithms can recognize visual cues such as head turns, and on-board processors can fuse this information with kinematic data for real-time predictions [74]. This multi-modal strategy enables earlier detection of potential conflicts and responses that feel natural to human road users. Research by Rasouli and Tsotsos (2019) reinforces these findings: models incorporating both visual and motion cues consistently outperformed those relying solely on motion data. This aligns with the current thesis, where non-kinematic indicators like head turns and gaze direction, combined with kinematic variables such as DTA, produced more accurate predictions overall [35].

Implementing advanced models in AVs requires improvements in sensor technology and algorithm design. Equipped with LiDAR, radar, and cameras, AVs can detect visual and motion cues, while deep learning techniques like CNNs process this data in real time [75]. Probabilistic models such as Bayesian inference address uncertainties like occlusion and sensor noise. However, challenges remain, including the need for computationally efficient algorithms and diverse training datasets to ensure models generalize across varied conditions. Combining BGT with machine learning can enhance predictive accuracy, enabling safer, more intuitive AV-cyclist interactions and fostering trust in automated systems.

The models developed in this thesis all have an open-box design, so it is obvious how specific variables influence interaction outcomes. While linear regression stands out for its ease of implementation and relatively low computational overhead—even when incorporating multiple variables—it may not capture the strategic, non-linear aspects of road user behavior effectively. BGT models, by contrast, handle more complex dynamics, but they are computationally more demanding, and the need to formulate appropriate payoff structures and accommodate diverse variables makes them more challenging to set up. Bayesian methods similarly offer strong interpretability through probabilistic outputs and the integration of prior knowledge, yet they can also demand significant computational resources and rigorous prior definitions. Ultimately, the choice of model hinges on balancing interpretability, data availability, and the inherent complexity of the interactions being studied.

Open-box models, such as linear regression, BGT, and Bayesian approaches, provide clear insight into how variables influence predictions, meet regulatory demands for transparency, and require less data compared to deep learning—ideal characteristics when labeled datasets are scarce or incomplete. Their comparatively lower computational overhead and simpler maintenance make them suitable for real-time deployment, while their explicit structures facilitate easier troubleshooting and iterative refinement. By handling strategic behavior and non-linear interactions without resorting to opaque network layers, these models strike a balance between complexity and clarity, which is particularly valuable in safety-critical or rapidly evolving scenarios where trust, transparency, and adaptability are paramount.

4.3.4 Regulations, policy, and educational interventions

The authorities responsible for regulations and policy making can enhance cyclists' safety in different ways. According to this thesis (as well as prior literature), speed stands out as a significant factor influencing interactions between cyclists and motorized vehicles, so controlling the speed of motorized vehicles is an obvious way to improve the road safety [76]. As reported in PAPER I, vehicles crossed the intersection first in 35% of cases, even when cyclists had priority. This finding highlights the need for educational programs (targeting both cyclists and drivers) to raise awareness about safe practices, right-of-way rules, and the importance of mutual respect. In addition, as mentioned, a specialized training program could be developed specifically for professional drivers, starting with a strong emphasis on understanding and obeying traffic laws—along with the consequences of any violations—and continuing to better familiarize them with cyclists and associated risk factors in high-conflict areas.

4.3.5 Consumer rating programs

Consumer rating organizations like Euro NCAP and IIHS are steadily refining their test protocols to better reflect real-world crash data and the latest research; these programs increasingly focus on VRUs—particularly at unsignalized intersections, where collisions often occur [15]. The models developed in this thesis can help verify the kinematic assumptions in current protocols and enable virtual assessments, which are especially valuable for AV safety evaluation. By emphasizing both kinematic factors and critical cyclist visual cues, these models offer a way to extend and refine existing test scenarios with realistic cyclist behavior. Furthermore, integrating these models into emerging digital testing procedures—such as Euro NCAP's shift toward virtual assessments—provides a flexible, cost-effective framework for capturing realistic cyclist interactions at intersections, ultimately streamlining safety evaluations and accelerating automated vehicle development.

By integrating the findings of this thesis, consumer testing can more accurately mirror real-world risks in interaction with cyclists. For example, Euro NCAP might require manufacturers to demonstrate how their vehicles detect and predict cyclist behavior at unsignalized intersections under various conditions. These conditions might include different visibility levels or arrival times at the intersection, reflecting the complexities observed in naturalistic and simulator data. Testing under more varied conditions would spur automakers to refine their perception and decision-making systems, ultimately promoting safer, more reliable interactions between automated vehicles and cyclists.

4.4 Implications for infrastructure design

There is a body of research investigating designs of intersections and roundabouts that are safer for cyclists [77]. In both roundabouts and unsignalized intersections, yielding behavior plays a crucial role in ensuring safe and smooth traffic flow [78][12]. Most of the work emphasizes dedicated bike lanes and speed control for motorized vehicles [76]. For example, Madsen et al. (2017) assessed the implications for cyclists' safety of various geometric configurations of biking lanes at intersections [79].

Visibility is one of the design elements. To date, the complete impact of this factor remains insufficiently understood [80], although previous research has demonstrated that restricted visibility significantly increases the risk of crashes between cyclists and motorized vehicles at intersections, obstructing the ability of both parties to anticipate each other's movements and intentions and leading to potential conflicts and collisions. Boda et al. (2018) pointed out that visibility plays a major role in drivers' behavior when interacting with cyclists at unsignalized intersections [11]. In this thesis, we examined the role of visibility on cyclists' response process during that interaction. In PAPER II, it was shown how extended visibility may result in less severe interactions between cyclists and motorized vehicles; in PAPER III, results indicated that better visibility can enhance drivers' yielding decisions, further improving the overall safety of the interaction. The findings of this thesis suggest that modifying existing intersections to provide better visibility would improve the safety of bicycle-vehicle encounters. By providing a concrete suggestion, this thesis has advanced traffic safety research one step further.

However, since visibility and speed are inseparably linked in traffic dynamics, reducing speed is an alternative countermeasure where physical modifications to improve sightlines are unfeasible or cost-prohibitive (e.g., where buildings obstruct the view). Indeed, research has consistently shown that lower speeds reduce collision severity and increase the time available for evasive maneuvers, particularly in locations with constrained sightlines [81].

The contributions of this thesis go beyond empirical support for the intuitive recognition that "more visibility is better." Through systematic observation, modeling, and experimentation, the results demonstrate *how* visibility influences the timing and nature of both cyclists' and drivers' reactions—particularly with respect to yielding behavior and overall interaction patterns. By pinpointing the configurations under which visibility is most crucial, this work lays the foundation for targeted interventions that extend beyond improvements to sightlines. For example, in cases where adjusting intersection geometry is impractical, speed-control measures (e.g., lower speed limits, traffic calming features) could help mitigate the risks caused by poor visibility [82]; implementing advanced warning systems, strategic road markings, and design elements encouraging thorough scanning behavior can further enhance safety in areas where opportunities to make physical alterations are limited [82].

Overall, addressing visibility and speed together holds the potential to significantly reduce serious conflicts between cyclists and motorized vehicles, fostering a safer coexistence on the urban roads. By exploring the nuanced ways in which visibility shapes road-user interactions, this thesis offers an evidence-based framework for developing interventions—whether through improved visibility, speed management, or a combination of both—that effectively reduce crash risks and promote safety for cyclists. Importantly, traffic-flow simulations and modeling would benefit from incorporating these micro-level interaction patterns, achieving more accurate assessments of network performance and more effective strategies for improving safety at a system-wide scale.

4.5 Limitations

As noted, all datasets used in this thesis have limitations. The number of interaction events in the ND data was limited due to data collection challenges.

In addition, finding and annotating interaction events in the ND data set was a time-consuming process that required significant human resources. Furthermore, video annotation in the ND data is subject to personal judgment, although we tried to minimize this effect by using multiple annotators. Another limitation in the ND dataset was the accuracy of the data. ND data was collected from one sensor, causing the measured distances to be less accurate for faraway objects than for closer ones. Further, the ND dataset was collected from one location in one country, which makes it hard to generalize the results—not only to the whole population, but also, certainly, to other countries.

The simulator's artificial environment engendered data that were less realistic than the ND data. There is a need to evaluate to what extent the results from the simulators match reality; for one thing, neither the bike nor car simulator had motion cues. In addition to their being less realistic, this feature may have been the cause of some participants dropping out due to motion sickness. (Further, the data collection for the riding simulator took place during the pandemic, which inevitably reduced the number of participants who enrolled in the study.) Future improvements to the simulators—such as integrating motion cues—could lead to more realistic interaction scenarios and fewer dropouts, permitting more robust conclusions.

While the developed models in this thesis used one instant in time to predict who crosses the intersection first, the complete interaction process is too complicated to be captured in a single moment. The decision whether to yield is the result of a series of interactions between the two road users; therefore, a continuous prediction model may be needed.

Another limitation is that this study addressed one specific scenario: a cyclist and a vehicle at right angles, both going straight (Figure 2). Although the selected scenario is quite common (and risky according to crash records), others also need attention (for example, a cyclist going straight encountering a vehicle turning right).

4.6 Future work

Future research can build upon these findings in several ways. First, collecting data from diverse locations in Sweden (and ideally, other countries) would improve the generalizability of the results, helping to verify that the identified interactions and variables hold true across different traffic cultures and infrastructural settings. In addition, future work may focus on models that can predict cyclists' yielding decisions in real time. Such a model can continuously inform AVs about the cyclists' decisions and plan accordingly. Third, future studies should consider more complex traffic scenarios involving multiple road users, capturing the interplay between cyclists, pedestrians, and various types of motorized vehicles. Finally, evaluating a broader range of vehicle-cyclist interaction scenarios—such as a right-turning vehicle versus a cyclist going straight—would offer a more comprehensive understanding of the factors influencing behavior and ultimately guide more robust design strategies for safer intersections and improved automated vehicle systems.

5 Conclusions

The overall objective of this PhD research was to investigate bicycle-vehicle interactions at unsignalized intersections and develop predictive models for their application in AD and ADAS to enhance cyclist safety.

Observations and experiments using both naturalistic driving (ND) and simulator data confirmed that kinematics and cyclists' visual cues are vital for anticipating cyclists' intentions at intersections. Notably, kinematics cues emerged as the most influential in predicting outcomes of these interactions. However, integrating visual cues into predictive algorithms further improved the prediction reliability of the models, offering an innovative solution beyond the kinematic-centric methods traditionally used in AD and ADAS.

By analyzing ND data, this research provided a foundational perspective on bicycle-vehicle interactions and the key factors influencing them. Building on these results, riding simulator experiments offered deeper insights into cyclists' responses to vehicles, elucidating their behavioral patterns and yielding decisions. In the final phase, predictive models were formulated to capture drivers' intentions toward cyclists, thereby contributing to a holistic view of bicycle-vehicle dynamics. Specifically, the thesis underscores how kinematic variables (e.g., DTA and visibility), cyclists' visual cues, and drivers' gaze metrics collectively determine interaction outcomes. Simulator findings further demonstrated the significance of non-verbal cues, reinforcing the benefits of combining objective measurements with subjective indicators for more human-centric AD. This integrated approach holds strong implications for safety technologies; incorporating gaze metrics and communicative behaviors into predictive models may help AD and ADAS predict both driver and cyclist actions at unsignalized intersections better. The findings also underscore the importance of non-verbal communication in enhancing the accuracy of threat assessment for AD and ADAS.

In addition, the naturalistic data further advanced our knowledge about the behavior of different driver types at intersections, revealing that professional drivers exhibit riskier behavior toward cyclists than do non-professional drivers: the former yielded less frequently.

Lastly, game-theoretic modeling proved to be highly effective for modeling bicycle-vehicle interactions, achieving greater accuracy with fewer parameters than traditional logit models. However, the game-theoretic approach introduces a higher level of complexity in model formulation and fitting, which may require more computational resources.

This thesis contributes to the AD field by advancing knowledge about bicycle-vehicle interactions and developing predictive models that can be utilized in AD and ADAS to predict, and possibly elicit, yielding behaviors. By incorporating both kinematic and behavioral data, these models can provide robust predictions of cyclist behavior and intention, thereby contributing to improved road safety.

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