QuantiBike: Quantifying Perceived Cyclists' Safety via Head Movements in Virtual Reality and Outdoors

Andrii Matviienko
andriim@kth.se
KTH Royal Institute of Technology
Stockholm, Sweden

Manuel Lehé
manuel.lehe@stud.tu-darmstadt.de
Technical University of Darmstadt
Darmstadt, Germany

Florian Heller
florian.heller@gmail.com
Independent Researcher
Aachen, Germany

Bastian Pfleging
bastian.pfleging@informatik.tu-freiberg.de
TU Bergakademie Freiberg
Freiberg, Germany

Max Mühlhäuser
max@tk.tu-darmstadt.de
Technical University of Darmstadt
Darmstadt, Germany

ABSTRACT

The current level of road safety for cyclists is estimated mainly based on police reports and self-reports collected during surveys. However, the former focuses on post-accident situations, while the latter is based on subjective perception and focuses only on road sections. This work builds the foundation to automatically assess perceived cyclists' safety by analyzing their head movements. In an indoor experiment (N = 12) using a Virtual Reality bicycle simulator, we discovered that perceived safety correlates with head rotation frequency and duration but not with head rotation angles. Based on this, we implemented a novel and minimalistic approach to detect head movements based on sensor data from Apple AirPods and an iPhone and conducted an outdoor experiment (N = 8). Our results indicate that perceived safety correlates with head rotation frequency and duration only at uncontrolled intersections when turning left and does not necessarily apply to all situations.

CCS CONCEPTS

• **Human-centered computing** → **Virtual reality**; **User studies**; **Empirical studies in HCI**.

KEYWORDS

cycling safety, head movements, virtual reality, cycling

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1 INTRODUCTION

Cycling safety is typically reflected in accident reports provided by the police. This implies that assessing dangerous road situations happens post-factum, i.e., after an accident has happened and a person has been injured. Cyclists' subjective perceived safety can differ from objective safety measures used for urban street design, defined as "individual's experience of the risk of becoming a victim of crime and disturbance of public order" [17]. To overcome this limitation of assessing cyclists' behavior on the go, we aim to quantify cyclists' safety before accidents happen by measuring and understanding their state.

Researchers have previously augmented bicycles and cyclists with additional sensors to quantify ride quality and estimate cyclists' proximity to other road users for safety reasons. They have employed eye-tracking to assess cyclists' attention and gaze behavior [25, 43], and smartphones to record rides [19]. More recent work quantified cyclists' peripheral awareness based on the brain's alpha waves to facilitate integration between cyclists and bicycles to increase safety [1, 45]. In contrast to the rather complex hardware required in these projects, we use common, off-the-shelf hardware. The broader availability of earables [20], i.e., in-ear headphones equipped with motion sensors, enable us to quantify head movements on a larger scale. The ear, in general, is an optimal spot to measure head movement as it is centered at the sides of the human head [9]. Although head movements typically indicate a shift in the users' attention, it still needs to be explored in the context of cycling and perceived safety. Therefore, this paper explores an additional way of quantifying perceived cyclists' safety based on head movements using data provided by built-in sensors from off-the-shelf earables and smartphones. We expect this data to contribute to crowdsourced bike-safety maps [19] and bike routing.

In this paper, we investigate the quantification of perceived cyclists' safety via head movements in Virtual Reality and outdoors. From the first experiment, in which participants cycled through four dangerous scenarios in a Virtual Reality bike simulator, we discovered that head rotation frequency and duration and not rotation angles reflect perceived cyclists' safety. To confirm this observation for the same scenarios outdoors, we developed and implemented a novel approach based on Apple AirPods worn by cyclists and an iPhone mounted on a bicycle to measure head movements relative to the body. The combination of these sensors provides a full picture of head movements given the static spatial relationship between bicycle and cyclist that form a single locomotion unit. Our results confirmed the findings from the indoor experiment that perceived safety correlates with head rotation frequency and duration but only at uncontrolled intersections when turning left.

Our main research contributions include the following:

- A novel and minimalistic approach to measure head movements via sensors from AirPods and an iPhone.
- An empirical evaluation of the proposed approach for assessing perceived cyclists' safety in Virtual Reality and outdoors.

2 RELATED WORK

This section outlines previous work focused on quantifying cyclists' movement, activity recognition via head movements, and evaluation environments for cyclists' behavior.

2.1 Quantifying Cyclists' Behavior

Cyclists' movement is important in understanding their decision-making process and identifying distractions in traffic. The gathered insights can suggest urban design improvements or develop new assistant systems, given that most of existing cyclists' assisting systems provide an output, such as warnings [26, 35, 46, 50], navigation cues [6, 15, 21, 28, 39, 49], and behavior recommendations [18, 27, 29], rather than input. The observable input data is vast, including eye and head movement, heart rate [51], and neural activity [1]. For example, Mantuano et al. [25] analyzed cyclists' gaze behavior and showed that intersections and crosswalks are less observed in the presence of pedestrians, and underlined the necessity of visual and physical separation for vulnerable road users. Eye and head movements are closely related and indicate visual attention [9]. For example, Rupi and Krizek [43] concentrated on the difference between experienced and inexperienced cyclists and found longer fixation times for experienced cyclists. The shorter fixation times of inexperienced cyclists signify active search strategies and a possible distraction from surrounding traffic. In this paper, we investigate head movements as an indicator of cyclists' perceived safety, since this correlation remains underexplored.

With the rise of the smartphone, new approaches leverage data from built-in sensors, such as accelerometers and gyroscopes, to assess road situations [41] and cyclists' behavior. For instance, Mohan et al. [37] used the accelerometer, microphone, and GPS to track the road and traffic conditions, e.g., honking and potholes. As for the cyclists' behavior, a project called BikeSafe [11] has shown that smartphones can effectively detect cyclists' dangerous behavior and prevent traffic accidents. Kawsar et al. [20] presented the open eSense earable platform[1] and its wide range of applications, such as understanding riders' behavior and contextual notifications. Ferlini et al. [9] have further investigated the eSense accuracy with its 6 degrees of freedom setup consisting of an accelerometer and gyroscope to track the head rotations of participants while standing. The tracking was accurate to a single-digit degree, even while chewing or talking as noise factors. Using earbuds, Ma et al. [24] found a way to detect steps, human activities, and face-tapping gestures through sound frequencies gathered via an inward-facing microphone. More recently, Karakaya et al. [19] developed the SimRa platform to record incidents and route data with a crowdsourcing approach.Their goal was better to understand cyclists' behavior and critical spots in cities to improve their perceived safety. They utilized the smartphone sensors to collect the GPS, accelerometer, and gyroscope data to automatically detect incidents, like near misses, where cyclists had to swerve quickly and map the cycled route. With this approach, they could gather an extensive database and detect problematic spots in Berlin. However, their approach focuses on the sensor data from the smartphone placed on a bicycle and the detection of situations caused by a sudden movement of the cyclist, e.g., swerving to the side or braking. It enables the detection of close passes or narrow misses, leaving recognition of motion for body parts out of the scope. In our work, we build on the idea of using a smartphone sensor data extended with the Apple AirPods 3[2] sensors to understand head movements and perceived safety.

[1] https://www.esense.io last access: 2023-03-14

2.2 Activity Recognition via Head Movements

One prominent way to study human activity involves understanding head motion patterns [8, 48]. From the recognition perspective, previous work primarily focused on the classification performance provided by machine and deep learning algorithms [13, 47] and proposed and improved existing computational models [8, 44]. From the human motion understanding, previous work explored the device technology [42], its placement [2], computational algorithms [54], inertial time series feature selection [54], and body rehabilitation [40]. As for exploring head movements of cyclists and motorcyclists, researchers focused on augmenting helmets with Inertial Measurement Units (IMUs) to detect head movements and improve the recognition rate [3, 14, 16] to send rescue requests and prevent accidents [4], leaving the understanding of riders' perceived safety out of the scope. For example, system families like Garmin or Apple aim to enhance the feeling of safety with accident detection systems[3] that inform emergency contacts or the local ambulance in case of critical events based on sensor data, e.g., spikes in the accelerometer data. However, they send notifications after accidents have already happened. Wong et al. [53] explored head motion recognition using a smart helmet for motorcyclists and introduced a methodology based on feature extraction from the IMU signal data to recognize four head motion patterns: looking up/down and turning left/right. However, the focus of their work lies on the high recognition of head movements rather than understanding what these head movements imply. Our work also analyzes the sensor data from IMUs integrated into an iPhone and AirPods 3. Still, we focus on understanding cyclists' head movements under exposure to dangerous traffic situations with a focus on perceived safety.

2.3 Evaluating Cyclists' Behavior

Two main approaches to evaluating cyclists' behavior are (1) simulated and (2) real-world naturalistic environments. The former typically involves a bicycle fixed on a platform in front of screens [22, 30] or using Virtual Reality glasses [36, 52] for the visual impression. The latter requires instrumented bicycles with additional hardware for outdoor environments. However, both of them fall under the

[2] https://www.apple.com/airpods, last access: 2023-01-15
[3] https://support.apple.com/en-us/HT213225

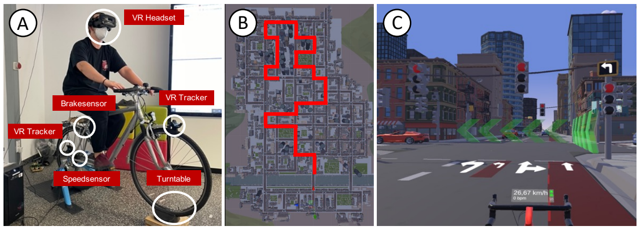

Figure 1: VR study overview: (a) The VR bicycle simulator consists of a bicycle on a fixed platform equipped with two VR trackers, speed- and brake sensors, a turntable, and a VR headset. (b) The route cyclists followed in the experiment. (c) Navigation indicators and road markings.

safety-realism trade-off [35], such that cycling on a bicycle simulator is safe but might be less realistic as in traffic and cycling in traffic is realistic but is not always safe. Although previous work explored methods to increase realism and safety in bicycle simulators [12, 38] and introduced AR- [34, 35] and tandem-based simulators [32, 33], the question of balancing cycling reality and safety is still open. To better understand the influence of both approaches on cyclists' head movements and perceived safety, we started by exposing participants to dangerous situations in the VR bicycle simulator. Afterward, we explored cyclists' behavior in the same scenarios outdoors and measured their head movements using our proposed approach based on an iPhone and AirPods. This comparison between lab and outdoor conditions allowed us to understand better the effects of both environments on cyclists' behavior.

3 STUDY 1: CYCLING IN VIRTUAL REALITY

We conducted a lab experiment in the Virtual Reality (VR) bicycle simulator under safe and immersive conditions to quantify cyclists' perceived safety via head movements. The research question for this experiment is: *"How do cyclists' head movements reflect their perceived safety while cycling in Virtual Reality?"*

3.1 Participants and Study Design

We recruited 12 participants (six female, six male) aged between 21 and 31 years (M = 24.67 years, SD = 2.74 years) using social networks and personal contacts. Three participants cycle daily, four once a week, three once a month, and two at least once a year. Half of them have previously experienced cycling in a bicycle simulator, and all use VR devices at least once a year. Participants did not receive any compensation for their participation.

For this study, participants cycled one route in a VR bicycle simulator that included four of the most dangerous situations based on previous work [31] and statistical reports [5, 10, 23]. These situations were: (1) a left turn at a traffic light-protected intersection, (2) a situation with road obstacles, e.g., a parked car on a shared bus & bike lane, (3) a situation in which a cyclist has to change her position within a lane (or even change lanes), which requires turning back to check the traffic behind, and (4) a cyclist is turning left at an uncontrolled intersection (Figure 3). All of these situations are described for right-hand traffic. These situations were repeated three times in a pre-defined order, and all participants experienced the same situation order during a ride. These parts of the route covered twelve (3 x 4) situations that we took for our analysis. Other 17 situations were mixed within the route and did not represent any of the above scenarios (Figure 1b). The route was 2.45 km long.

3.2 Apparatus

We conducted the experiment in a VR bicycle simulator, which consisted of a bicycle (28-inch) placed on a *Tacx Satori Smart Trainer*[4] with a 1.6 kg flywheel. The front wheel was placed on a turntable to facilitate the rotation of the handlebar in a static position. Cycling actions, such as steering, pedaling, and braking, were reflected in the simulation shown in a VR head-mounted display (Valve Index). The VR environment was implemented using Unity SDK (2020.1.12f1) and SteamVR assets and consisted of a virtual city in a flat landscape. The bicycle was fitted with a Garmin Speed Sensor 2 that transmits real-time speed via ANT+ and a brake sensor that consisted of an ESP-WROOM-32 and a TTP223 capacitive touch sensor on the rear wheel connected via USB (Figure 1a).

The cycling simulation contained traffic lights and car flows, simulated by an existing Traffic Simulation project that enables easy traffic simulation in a scene[5]. We adjusted this asset to account for a cyclist in the traffic flow, e.g., a car will stop if a cyclist has a right to turn first. To facilitate an adequate performance of the simulation environment, we spawned the cars based on the triggers placed in the environment to facilitate the traffic flow at the locations near the cyclist. Similarly, the cars were despawned when a cyclist reached a despawning trigger placed in the environment or when a car was out of cyclists' viewing angle.

The cars followed traffic rules, such as red/green traffic lights, stayed within the street layout, and kept a safe distance from other cars in front of them.

Additionally, the simulation contained green arrows placed in the environment to navigate a cyclist throughout the city (Figure 1c).

3.3 Measurements

To quantify cyclists' perceived safety via head movements, we measured the following dependent variables:

- **Head rotation angle**: we measured head rotation azimuth angles with a Virtual Reality HMD. 0° is the nose with the deadband range from -20° to +20° (Figure 2) to filter out smaller head rotations possibly caused by body movements during cycling. The value of 20° was based on pilot testing before the experiment. We did not use any other filters.
- **Head rotation frequency**: we counted the number of head rotations left and right larger than 20° (Figure 2).
- **Head rotation duration**: we calculated the duration of head rotations left and right using a Virtual Reality HMD, i.e., a time between a head leaving the 20° threshold and coming back to it (Figure 2).
- **Total duration at situations**: we measured the participant's total time in each situation. For this, we added boundary boxes around each situation. The timer started when a bicycle's front wheel entered the boundary box and stopped when the rear wheel left it.

[4]https://www.garmin.com/en-US/p/690891
[5]https://github.com/mchrbn/unity-traffic-simulation

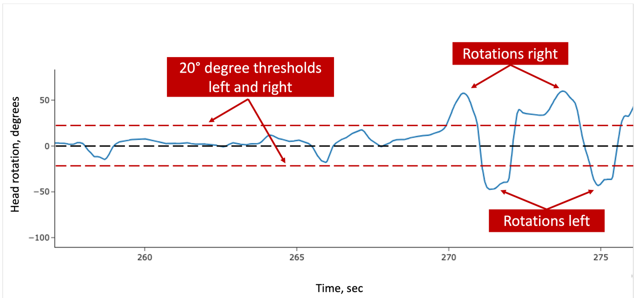

Figure 2: We counted rotations outside the threshold of 20° to left or right as a head rotation. The threshold of 20° was selected to filter out small head movements, possibly unrelated to traffic situations. The reported angle for the registered rotation is the highest/lowest value in the range. Due to the drifting of the sensor data outdoors, we calculated the mean rotation for every minute and used this as a neutral value.

- **Total duration standing at situations**: we measured the total time participants spent standing at each situation, i.e., when the velocity was zero, as an indicator of the amount of time necessary to make a decision.
- **Perceived safety**: participants rated how safe they felt in each situation using a 5-point Likert scale (1 – very unsafe, 5 – very safe) per category of situations, i.e., four times.

3.4 Procedure

After obtaining informed consent, we collected participants' demographic data and explained the experiment's goal. Their task was to cycle through the virtual city by following the navigation arrows placed in the environment (Figure 1 c), and follow the traffic rules. At the end of the study, we interviewed the participants about their perception of safety and the difficulty by showing them the four experienced scenarios and by asking them to justify their perceived safety score. The entire study took approximately 30 minutes.

3.5 Data analysis

In both experiments, we used a one-way ANOVA and t-tests for post-hoc analysis of the parametric data since all assumptions for the parametric data analysis were met. We applied a Friedmann test and a Wilcoxon signed-rank test for non-parametric data. For multiple comparisons analysis, we used a Bonferroni correction. For the correlations, we used Spearman's rank correlation coefficient.

3.6 Quantitative results

The summary of results is shown in Table 1 and Figure 4.

3.6.1 Head rotation angle. Cyclists had the largest head rotation angles to the *left* for situations with obstructed lanes ($Md = 124°, IQR = 56°$), followed by intersections with pockets ($Md = 63°, IQR = 32°$), turning left at uncontrolled intersections ($Md = 50°, IQR = 33°$), and lane changing ($Md = 47°, IQR = 23°$). This difference is statistically significant, as shown by a Friedman test ($\chi^2(3) = 8.3, p < 0.05$, $\eta^2 = 0.34$). The post-hoc analysis shows that situations with obstructed lanes are statistically significantly different compared to the other three situations ($p < 0.05$). The remaining pairwise comparisons do not reveal statistically significant differences ($p > 0.05$). In contrast, cyclists had similar head rotation angles to the *right* across all scenarios: obstructed lanes ($Md = 24°, IQR = 31°$), intersections with pockets ($Md = 38°, IQR = 17°$), lane changing ($Md = 35°, IQR = 13°$), and turning left at uncontrolled intersections ($Md = 41°, IQR = 8°$). Thus, a Friedman test did not indicate a statistically significant difference ($\chi^2(3) = 3$, $p > 0.05$, $\eta^2 = 0.17$).

Table 1: The VR study results: median head rotation angles, frequencies, duration left and right, total time spent at situations and time spent standing, and perceived safety. Angle = Head rotation angle, Freq. = Head rotation frequency, Dur. = Head rotation duration, Stand. = Time spent standing, Total = Total time spent at situations, S = safety.

Scenario	Angle		Freq.		Dur.		Time		S
	L	R	L	R	L	R	Stand.	Total	
A: Left turn at intersections with pockets	63°	38°	3	1	3	1	12	25	4
B: Obstructed lane	124°	24°	1	0	0.5	0	1	8	4
C: Lane change for turning left	47°	35°	2	1	1	1	9	21	3
D: Left turn at uncontrolled intersections	50°	41°	3	2	1	1	6	15	2

3.6.2 Head rotation frequency. Cyclists turn their heads *left* less frequently when overtaking obstacles on obstructed lanes ($Md = 0.5, IQR = 1$) than when turning left at intersections with pockets ($Md = 3, IQR = 1.3$), uncontrolled intersections ($Md = 2.8, IQR = 3.4$), or changing a lane ($Md = 2, IQR = 2.75$). This finding is confirmed by a statistically significant difference using a Friedman test ($\chi^2(3) = 18.6, p < 0.001, \eta^2 = 0.52$). The post-hoc analysis reveals a significant difference between the situation with obstructed lanes and the remaining situations ($p < 0.05$). For rotation frequency to the *right* side, cyclists have fewer rotations when going around obstacles ($Md = 0.3, IQR = 0.5$) compared to turning left at intersections with pockets ($Md = 1.2, IQR = 1.1$), uncontrolled intersections ($Md = 1.6, IQR = 3.6$), or changing a lane ($Md = 1.2, IQR = 1.3$). This finding is confirmed by a statistically significant difference using a Friedman test ($\chi^2(3) = 8.8, p = 0.032, \eta^2 = 0.24$) and the post-hoc analysis between the situation with obstructed lanes and the remaining situations ($p < 0.01$). The remaining pairwise comparisons for left and right head rotation frequencies do not reveal any statistically significant difference ($p > 0.05$).

3.6.3 Head rotation duration. Head rotations left were, on average, longer at intersections with pockets ($Md = 3.25$ sec, $IQR = 2.4$), followed by lane changing ($Md = 1.3$ sec, $IQR = 0.5$), uncontrolled intersections ($Md = 1.3$ sec, $IQR = 0.5$), and obstructed lanes ($Md = 0.5$ sec, $IQR = 1.1$). This finding is confirmed by a statistically significant difference using a Friedman test ($\chi^2(3) = 24.1, p < 0.001, \eta^2 = 0.67$). The post-hoc analysis reveals a significant difference between all the situations ($p < 0.001$), except lane changing and uncontrolled intersections ($p > 0.05$). Head rotation duration to the right is comparable among intersections with pockets ($M = 0.97$ sec, $SD = 0.75$), obstructed lanes ($M = 0.42$ sec, $SD =$

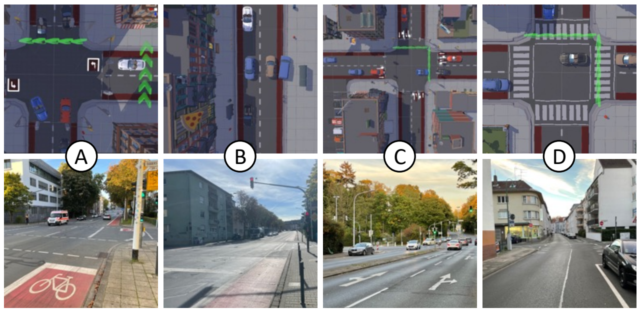

Figure 3: Four scenarios shown in VR (upper row) and outdoors (lower row): (a) Left turn at intersections with pockets, (b) Obstructed bicycle lanes, (c) Lane Change for Turning Left, and (d) Left turn at uncontrolled intersections.

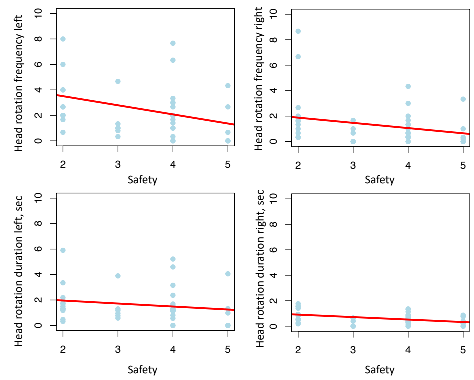

Figure 4: Correlations in VR (over all situations) between perceived safety and head rotation frequencies and duration.

0.41), lane changing ($M = 0.62$ sec, $SD = 0.41$), and uncontrolled intersection ($M = 0.78$ sec, $SD = 0.62$). A one-way ANOVA test does not reveal statistical differences among the situations ($p > 0.05$).

3.6.4 Total duration at situations. Cyclists spent the least amount of time at the situation with obstructed bicycle lanes ($Md = 8$ sec, $IQR = 4$), followed by a left turn at uncontrolled intersections ($Md = 15$ sec, $IQR = 16$), lane changing ($Md = 21$ sec, $IQR = 13$), and left turn at intersections with pockets ($Md = 25$ sec, $IQR = 10$). Using a Friedman test, we discovered that this difference is statistically significant ($\chi^2(3) = 24, p < 0.001, \eta^2 = 0.68$) and the post-hoc analysis shows differences for all pairs ($p < 0.05$).

3.6.5 Total duration standing at situations. Participants spent less time making decisions on obstructed bicycle lanes ($Md = 1$ sec, $IQR = 1.8$), followed by a left turn at uncontrolled intersections ($Md = 6$ sec, $IQR = 17$), lane change ($Md = 8.7$ sec, $IQR = 11$), and left turn at intersections with pockets ($Md = 12$ sec, $IQR = 9$). We discovered that this difference is statistically significant using a Friedman test ($\chi^2(3) = 18.4, p < 0.001, \eta^2 = 0.51$). The post-hoc analysis shows that cyclists waited the shortest amount of time on obstructed bicycle lanes compared to all situations ($p < 0.001$). Moreover, cyclists waited longer at intersections with pockets than at uncontrolled intersections ($p = 0.015$). The remaining pairwise comparisons are not statistically significant ($p > 0.05$).

3.6.6 Perceived safety. Turning left at intersections with pockets ($Md = 4, IQR = 2$) and situations with obstructed lanes ($Md = 4, IQR = 2$) feels safer than lane changing for turning left ($Md = 3, IQR = 2$) and turning left at uncontrolled intersections ($Md = 2, IQR = 1.5$). However, this difference is not statistically significant, as shown by a Friedman test ($\chi^2(3) = 7.5, p = 0.058, \eta^2 = 0.2$).

3.6.7 Correlations. Using Spearman's rank correlation coefficient, we analyzed the perceived safety over all situations together and separately. Summarized over all situations, we discovered a statistically significant correlation between perceived safety and head rotation frequencies left ($r_s = -0.43, p < 0.01$) and right ($r_s = -0.31, p < 0.05$). Moreover, we observed a statistically significant correlation between the perceived safety and head rotation duration left ($r_s = -0.34, p < 0.05$) and right ($r_s = -0.37, p < 0.01$). However, the correlation is not statistically significant between perceived safety and head rotation angles left ($r_s = -0.12, p > 0.05$) and right ($r_s = -0.12, p > 0.05$). Lastly, the correlation is statistically significant between perceived safety and total duration at situations ($r_s = -0.35, p < 0.05$) and total duration standing at situations ($r_s = -0.4, p < 0.01$). As for each situation, there is a statistically significant correlation between perceived safety and head rotation frequency to the left for situations with obstructed lanes ($r_s = -0.57, p = 0.049$) and lane changing ($r_s = -0.57, p = 0.049$). For the lane-changing situation, a statistically significant correlation exists between perceived safety and total time ($r_s = -0.58, p = 0.044$) and time standing in the situation ($r_s = -0.58, p = 0.044$). The remaining correlations are not statistically significant ($p > 0.05$).

3.7 Qualitative results

3.7.1 Scenario A: Left turn at intersections with pockets. For this traffic scenario, participants reported difficulties understanding the traffic flow from the right, recognizing hazardous situations, and acting safely. Additionally, they mentioned that getting an overview of the whole intersection was problematic, and they had to look around for some time to assess the situation. However, it was easy to enter the pocket, and they had traffic lights to help make a crossing decision. For example, participants mentioned that: *"getting an overview of the traffic in this situation was difficult"* [P7], *"it was challenging to keep the whole intersection in sight"* [P8], and *"It was overwhelming because I had to observe traffic flows twice: when entering and when leaving the pocket."*[P11]. Regarding the safety concerns, participants noted that it was difficult to estimate a moment to make a decision, crossing an orthogonal traffic flow was scary, and a concern not to be seen by others. For instance, they mentioned: *"Because there were so many impressions and I did not quite know when I could go."* [P12], *"I had to move in front of the orthogonal traffic, which can be scary, especially on big streets."*[P6], and *"I had the feeling to be overlooked very easily."* [P9].

3.7.2 Scenario B: Obstructed bicycle lane. This traffic scenario was very familiar to participants from real-world situations, and they had to do a shoulder look before overtaking a parked car on the bicycle lane. However, they reported that they lacked awareness of the situation, had to slow down before looking over a shoulder and keep a distance from a car in case somebody opened a door. For example, participants mentioned that *"Only by looking over my shoulder was it clear whether I could change to the traffic lane."* [P2], *"I would drive rather slowly in this situation to have enough time to do multiple safety looks over the shoulder to be sure to not collide with any cars approaching from behind."* [P6], and *"I remember that a door of the stationary vehicle can also open."* [P9].

3.7.3 Scenario C: Lane change for turning left. For this traffic scenario, participants expressed concerns about changing to the left-most lane ahead of time, cars approaching from behind, and the need for constant head movements to look around. Time coordination for lane changing was problematic since failing it leads to a decreased feeling of safety. Some participants noted: *"Hard to see the lane, I have to decide to cross very early, especially if there are a lot of cars on the road"* [P1], *"Cars from behind make me feel unsafe, especially when driving into their path and crossing their lane"* [P4], and *"[it was] a bit difficult because I had to switch to the car lane instead of staying in the bike lane. You must pay attention to the cars behind, beside, and in front of you."* [P5].

3.7.4 Scenario D: Left turn at uncontrolled intersections. In this traffic scenario, participants needed help assessing the traffic and making a decision based on the traffic flow from all directions, which made them feel unsafe. They mentioned fear of being overseen by car drivers and an issue of estimating the time to cross a given gap. As some participants mentioned: *"You have to expect traffic from all directions."* [P2], *"I still had to watch out for oncoming traffic, and from the feeling here, I felt a little unsafe because I didn't know what the oncoming traffic was doing."* [P11], and *"Cars from all sides and even those in my lane made me feel unsafe."* [P4].

3.8 Discussion

Our results indicate that head movements reflect cyclists' perceived safety in the Virtual Reality bicycle simulator. The frequency and duration of head rotations are more essential indicators of perceived safety than their size. Regardless of how big or small the angles of head rotations are, their frequency and duration indicate cyclists' feeling of safety. More specifically, the higher the frequency of head rotations, the lower the perceived safety. Similarly, the higher the duration of head rotations, the lower the perceived safety. Apart from head movements, the time spent in situations (total or standing) indicates cyclists' perceived safety. The more time cyclists spend in situations, the less safe they feel. In other words, they spend more time in a situation if it makes decision-making difficult. Looking at the duration spent at situations was rather exploratory and requires further exploration in the future. We also found that cyclists felt safer in situations they are more familiar with (obstructed bicycle lane) or with a dedicated infrastructure (safety pocket). While the former situation demonstrates an issue of many parked cars on the side of the road, the latter shows that cyclists need a dedicated place on the road not only while cycling but also while turning. The other two scenarios related to lane changing and turning left at uncontrolled intersections cause a lower feeling of safety. This can be explained by a more complex decision-making process that requires checking traffic flows from different directions, which can be time-consuming and mentally demanding.

As for each traffic situation, head rotation frequency in situations with obstructed lanes and lanes changing negatively correlates with perceived safety. Both situations are similar since they require a shoulder look to check the traffic behind them. In situations with a lot of traffic, as in our experiment, cyclists felt unsafe overtaking a car parked on a bicycle lane or changing lanes. Interestingly, the angle size differs among these situations because cyclists prepare for lane changing ahead of time, while overtaking an obstacle on a bicycle lane might require little preparation. This finding reveals that to quantify cyclists' behavior, we need to analyze their behavior in these situations and before them. How big this time frame should be will depend on the type of situation and is a question for future research.

Our results show that cycling on a bicycle lane with an obstacle can be detected based on head rotation angle and frequencies compared to the other three scenarios. On average, cyclists make one shoulder look to check for upcoming traffic behind them, which leads to a head rotation angle of about 124°to the left. When cyclists change a lane for turning left or turn left on uncontrolled intersections with or without safety pockets, the head rotation angle lies in the range of [47°; 63°] with a frequency of rotation of around 2-3 times to the left. Moreover, the latter three scenarios require a longer time to make a crossing or turning decision (total and standing). This might be explained by the higher complexity of these situations due to upcoming traffic from different directions and occasional traffic lights that require cyclists to spend longer in these situations. Thus, situations with obstructed bicycle lanes can easily be detected based on the sensor data from head movement angles and frequency. Situations that require turning left at intersections or while lane changing look similar regarding head rotations and might need a larger time frame for the data or an additional quantifier based on the sensor data, e.g., eye tracking.

This experiment helped us understand cyclists' perceived safety in different traffic scenarios via head movements. However, it was conducted in a controlled environment that does not account for random traffic situations. Thus, we conducted a consequent field experiment exploring a novel approach to detect head movements via AirPods and an iPhone, which we describe in the following.

4 APPROACH FOR MEASURING HEAD ROTATIONS USING IPHONE AND AIRPODS

To measure head rotations while cycling outdoors, we developed and implemented a concept based on iPhone and Airpods 3 sensors. We placed an iPhone on the non-moving part in front of a bicycle and AirPods in the participant's ears. The smartphone provides a better understanding of bicycle movements, and the AirPods reflect cyclists' head movement. Since both a bicycle and a cyclist create one locomotion unit and are placed in the same relation towards each other, the combination of the sensor data provides a full picture of head movements. The Inertial Measurement Units inside both devices allow for measuring individual device rotations, and the subtraction of these rotations provides the head rotation. The AirPods form a 6 DoF system and allow the rotation calculation based on the accelerometer ($x_{acc}, y_{acc}, z_{acc}$) and the gyroscope data ($x_{gyro}, y_{gyro}, z_{gyro}$). The iPhone has 9 DoF with an additional 3 DoF from the magnetometer ($x_{mag}, y_{mag}, z_{mag}$). To calculate a yaw

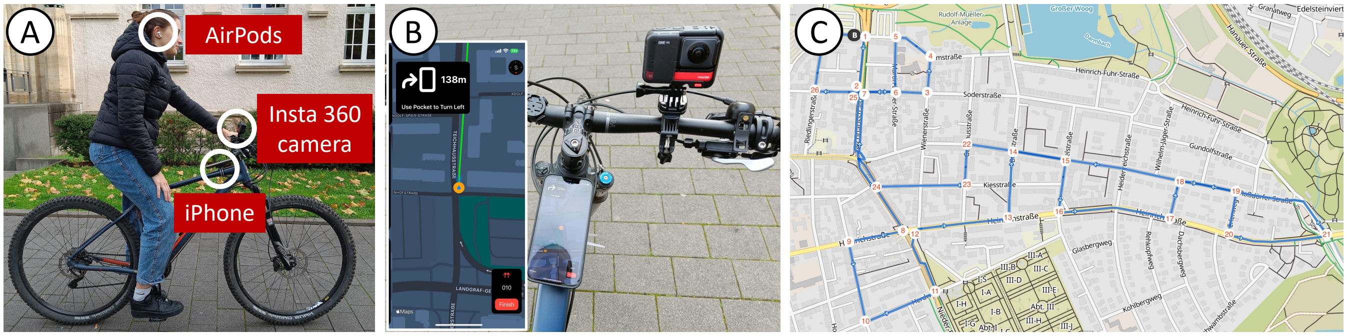

Figure 5: Field study: (a) Participant wearing AirPods on a bicycle with an iPhone and Insta 360 camera. (b) A bicycle with a smartphone showing navigation directions and a screenshot from the app. (c) A route cyclists followed in the experiment.

value relative to the bike rotations reflected by the iPhone rotation matrix, we used Diebel's formula [7]. We used the rotation matrices from Apples Core Motion[6] for the iPhone (P) and the AirPods (A):

$$M_{\mathrm{P}} = \begin{pmatrix} mp_{11} & mp_{12} & mp_{13} \\ mp_{21} & mp_{22} & mp_{23} \\ mp_{31} & mp_{32} & mp_{33} \end{pmatrix}; M_{\mathrm{A}} = \begin{pmatrix} ma_{11} & ma_{12} & ma_{13} \\ ma_{21} & ma_{22} & ma_{23} \\ ma_{31} & ma_{32} & ma_{33} \end{pmatrix}$$

To calculate a rotation matrix relative to the bicycle, we multiplied the iPhone's rotation matrix by the AirPods' inverted rotation matrix:

$M_{\mathrm{AngleRelativeToiPhone}} = M_{\mathrm{P}} M_{\mathrm{A}}^{-1} = M_{\mathrm{P}} M_{\mathrm{A}}^{T}$.

$M_{\mathrm{AngleRelativeToiPhone}}$ provides final Euler angles as follows:

- $Yaw = \psi(M_{\mathrm{AngleRelativeToiPhone}}) = atan2(M_{12}, M_{11})$
- $Roll = \phi(M_{\mathrm{AngleRelativeToiPhone}}) = atan2(M_{23}, M_{33})$
- $Pitch = \theta(M_{\mathrm{AngleRelativeToiPhone}}) = -asin(M_{13})$

Compared to complicated and often bulky solutions, the proposed approach is minimalistic and accessible to quantifying cyclists' behavior. Since many previously proposed assistive technology for cyclists have focused on the output [26–29, 35], this solution creates a ground for using output systems, e.g., warnings on demand without mentally overloading cyclists.The concept can also be used to communicate cyclists' behavioral states to other users for safety reasons, e.g., a cyclist did not see an upcoming car.

5 STUDY 2: CYCLING OUTDOORS

To evaluate our proposed approach and verify the findings from the first experiment, we conducted a field study in which participants cycled outdoors in traffic. The research question for this experiment is: *"To what extend can we use cyclists' head rotations to quantify their perceived safety under real traffic conditions*?"

5.1 Participants and Study Design

We recruited eight participants (2 female, 6 male) aged between 22 and 28 years ($M = 24.8$ years, $SD = 1.9$ years) using social networks and personal contacts. Five participants participated in our VR study. Two participants cycle every day, two participants once a week, and four once a month. Four participants described themselves as safe cyclists, and the other four as medium-safe cyclists. Participants did not receive any compensation for their participation.

Participants cycled one route (5.5 km) in a medium-sized European city in right-hand traffic that included the four most dangerous situations in a pre-defined order as investigated in the first experiment (Figure 3) based on previous work [31] and statistical reports [5, 10, 23]. Unlike the cycling route in the VR experiment, these situations were repeated two times for turning left with intersection pockets, obstructed lanes, and lane changing and nine times for turning left at uncontrolled intersections to avoid a long cycling route. Participants' task was to safely ride a bicycle along the predefined route displayed on the smartphone on the handlebar. The study took place on sunny days outside peak hours (between 10 am and 3 pm) to avoid large traffic flows for safety reasons and to create comparable cycling conditions for all participants.

5.2 Apparatus

We used a bicycle (29-inch wheel) with an iPhone on the handlebar (Figure 5 a and b) and provided participants with AirPods 3 connected to the iPhone. We installed a self-developed iOS application on the iPhone to measure rotations for both the iPhone and AirPods in the background and a custom navigation application similar to Google Maps showing a pre-defined route (Figure 5c) in the foreground [7]. The navigation included vocal turn-by-turn instructions presented through the AirPods and a constantly updated screen showing the distance to the next turn and a green line indicating the route (Figure 5b). We logged rotations of iPhone and AirPods during the whole ride duration. Additionally, we placed an Insta360 ONE RS camera[8] on the bicycle's handlebar to record the cyclists' behavior and environment. The video feed served as ground truth to assess our approach using the head rotation data (Figure 5b).

5.3 Measurements

We measured the same dependent variables as in the previous study for consistency and comparability. However, we measured the head rotation angle, frequency, and duration using iPhone and AirPods.

5.4 Procedure

After obtaining informed consent, we collected the participants' demographic data, explained the experiment's goal, and provided

[6]https://developer.apple.com/documentation/coremotion

[7]https://github.com/Nomandes/quantibike

[8]https://www.insta360.com/de/product/insta360-oners

Table 2: The field study results: median head rotation angles, frequencies, and duration left and right, total time spent at situations and time spent standing, and perceived safety. Angle = Head rotation angle, Freq. = Head rotation frequency, Dur. = Head rotation duration, S = Safety.

Scenario	Angle		Freq.		Dur.		Time		S
	L	R	L	R	L	R	Stand.	Total	
A: Left turn at intersections with pockets	43°	34°	4.5	3.5	1.3	1.4	30	54	4
B: Obstructed lane	–	–	–	–	–	–	–	–	–
C: Lane change for turning left	47°	33°	2	1.5	0.4	0.4	4	28	3.5
D: Left turn at uncontrolled intersections	41°	45°	3	2	1	1	5	22	4.5

an opportunity to ride on the bicycle for familiarization purposes. The task was to cycle through the city by following the visual and auditory navigation on the smartphone and the AirPods (Figure 5a). Participants were instructed to cycle safely and be considerate regarding vehicles. After the ride, the participants indicated their perceived safety in the experienced scenarios and justified their score. The study lasted approximately one hour per participant.

5.5 Data analysis

For the video analysis, one of the co-authors annotated the videos second-by-second based on the start and end of a head rotation, which included: (1) looking at the start second and watching whether the person rotated a head and (2) when participants rotated their head, minutes and seconds from start to finish were marked on the video. These annotations were compared to the head rotations detected with Airpods and iPhone. We excluded situations with obstructed lanes because participants did not experience them despite our deliberate attempts to guide them through streets with many parked cars. The reality shows that participants cycled in the middle of the roads with many parked cars because there was not much traffic, and a shoulder look was unnecessary. Therefore, we outline the results for the remaining three scenarios.

5.6 Quantitative results

The summary of results is shown in Table 2 and Figure 6.

5.6.1 Head rotation angle. Participants had the largest head rotation angles to the *left* when changing lanes ($Md = 47°, IQR = 35$), followed by turning left at uncontrolled intersections ($Md = 41°, IQR = 9$) and intersections with pockets ($Md = 43°, IQR = 14$). However, this difference is not statistically significant as shown by a Friedman test ($\chi^2(2) = 0.25, p > 0.05, \eta^2 = 0.02$). Similarly, cyclists had the largest rotation angles to the *right* when changing lanes ($Md = 33°, SD = 53$), followed by turning left at uncontrolled intersections ($Md = 45°, IQR = 12$) and intersections with a pocket ($Md = 34°, IQR = 5$). This difference is not statistically significant as shown by a Friedman test ($\chi^2(2) = 2.57, p > 0.05, \eta^2 = 0.18$).

5.6.2 Head rotation frequency. Cyclists turn their heads *left* more frequently when turning left at intersections with pockets ($Md = 4.5, IQR = 3.375$), followed by uncontrolled intersections ($Md = 3, IQR = 1$) and when changing a lane ($Md = 2, IQR = 1.5$). This differences is not statistically significant as shown by a Friedman test ($\chi^2(2) = 2.4, p > 0.05, \eta^2 = 0.15$). For rotation frequency to the *right*, cyclists had more rotations when turning left at intersections with pockets ($Md = 3.5, IQR = 3.75$), followed by uncontrolled intersections ($Md = 1.7, IQR = 1$) and changing a lane ($Md = 1.5, IQR = 2.38$). This difference is not statistically significant as shown by a Friedman test ($\chi^2(2) = 2.4, p > 0.05, \eta^2 = 0.15$).

5.6.3 Head rotation duration. Head rotations to the left were shorter when changing a lane ($Md = 0.4sec, IQR = 0.2$) than at intersections with pockets ($Md = 1.3sec, IQR = 0.6$) and uncontrolled intersections ($Md = 1sec, IQR = 0.3$). This differences is statistically significant as shown by a Friedman test ($\chi^2(2) = 7.8, p < 0.05, \eta^2 = 0.5$). The post-hoc analysis reveals a statistically significant difference between lane changing and uncontrolled intersections ($p < 0.05$) and intersections with pockets ($p < 0.05$), but not between intersections with pockets and uncontrolled intersections ($p > 0.05$). Head rotations to the right when changing lane were shorter ($Md = 0.4sec, IQR = 0.2$) compared to uncontrolled intersections ($Md = 1sec, IQR = 0.4$) and intersections with pockets ($Md = 1.4sec, IQR = 0.5$). This finding is statistically significant as shown by a Friedman test ($\chi^2(2) = 10.8, p < 0.05, \eta^2 = 0.7$). All pairwise comparisons are statistically significant ($p < 0.05$).

5.6.4 Total duration at situations. Participants spent less time at uncontrolled intersections when turning left ($M = 22sec, SD = 4$) than lane changing ($M = 28sec, SD = 14$) and turning at intersections with pockets ($M = 54sec, SD = 24$). Using a One-way ANOVA, we found that this difference is statistically significant ($F(2, 21) = 7.9, p < 0.001$). The post-hoc analysis shows a statistically significant difference between turning left at uncontrolled intersections and intersections with pockets ($p < 0.05$). The remaining pairwise comparisons are not statistically significant ($p > 0.05$).

5.6.5 Total duration standing at situations. Cyclists waited the longest at intersections with pockets ($Md = 30sec, IQR = 32$), followed by lane changing ($Md = 4sec, IQR = 12$) and left turn at uncontrolled intersections ($Md = 5sec, IQR = 2$). This finding is statistically significant as shown by a Friedman test ($\chi^2(2) = 6.8, p < 0.05, \eta^2 = 0.42$). The post-hoc analysis shows that cyclists waited at intersections with pockets statistically longer compared to the other two situations ($p < 0.05$). The remaining pairwise comparisons are not statistically significantly different ($p > 0.05$).

5.6.6 Perceived safety. Perceived safety was comparable with turning left at uncontrolled intersections being the highest ($Md = 4.5, IQR = 1.25$), followed by turning left at intersections with pockets ($Md = 4, IQR = 1$) and lane changing ($Md = 3.5, IQR = 1.25$). This finding is confirmed by a statistically non-significant difference shown by a Friedman test ($\chi^2(2) = 5.2, p > 0.05, \eta^2 = 0.32$).

5.6.7 Correlations. We analyzed the perceived safety over all situations together and separately. Summarized over all situations, unlike the indoor experiment, we did not find statistically significant correlations between perceived safety and head rotation frequencies left ($r_s = -0.2, p > 0.05$) and right ($r_s = -0.15, p > 0.05$) as well as head rotation duration left ($r_s = -0.13, p > 0.05$) and right ($r_s = -0.31, p > 0.05$) Figure 6. The correlation is not statistically

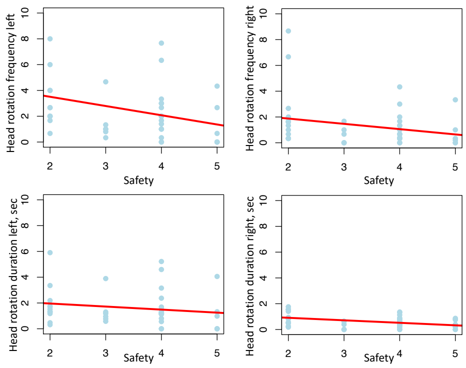

Figure 6: Correlations outdoors (over all situations) between perceived safety and head rotation frequencies and duration.

significant between perceived safety and total duration at situations ($r_s = -0.02, p > 0.05$) and total duration standing at situations ($r_s = -0.1, p > 0.05$). Similarly to the indoors, the correlation is not statistically significant between perceived safety and head rotation angles left ($r_s = -0.12, p > 0.05$) and right ($r_s = -0.12, p > 0.05$). As for each individual situation, there is a statistically significant correlation between perceived safety and head rotation frequency to the left ($r_s = -0.49, p < 0.05$) and right ($r_s = -0.75, p < 0.05$) for the turning left at uncontrolled intersections. Moreover, for the left turn at uncontrolled intersections, we observed a statistically significant correlation between perceived safety and head rotation duration to the left ($r_s = -0.75, p = 0.03$) and right ($r_s = -0.88, p < 0.05$) for the lane changing situation. The remaining correlations are not statistically significant ($p > 0.05$).

5.7 Qualitative results

5.7.1 Scenario A: Left turn at intersections with pockets. Cyclists experienced few difficulties since it was easy to understand how to use the pocket. They could disregard the approaching traffic flow and had sufficient isolation from it. As they noted: *"Easy to understand concept of left turn"* [P2], *"It is very clear where to go as a cyclist and you have to worry less about oncoming traffic."* [P3], and *"You get isolated from the rest of traffic if merging into a pocket. No communication with other drivers needed, no waiting time in the middle crossroad."* [P6]. Cyclists felt safe due to a separate bicycle lane and clear indications regulated by a traffic light. However, participants sometimes felt unsafe because they needed to know if other road users knew and understood intersections with pockets for cyclists. As some mentioned: *"The only thing that unsettled me was that I had the feeling that other road users did not know the pocket and were surprised why I was standing there."* [P3], *"Everything was regulated by a traffic light and you did not have to cross the traffic"* [P5], and *"It feels safe to have a dedicated space for bicycles."* [P6].

5.7.2 Scenario C: Lane change for turning left. This scenario was perceived as rather difficult due to the necessity to estimate traffic in the front and behind. As participants mentioned: *"[I] needed to take a look at the traffic behind me, need to switch lanes, need to know this sometime before the crossroads"* [P1] and *"Stressful, especially if you realize too late that you should have gotten into the left lane. If the road is busy, I would prefer to drive on the sidewalk and turn left at the traffic lights."* [P3]. They have also noted the importance of a good overview of the situation and arrow markings on the road. As some commented: *"You need a good view and have to calculate when you can turn left."* [P7] and *"Street arrows show where to go"* [P3.] Cyclists felt unsafe due to the danger of cars approaching from behind and active traffic observations. As some mentioned: *"Sometimes other drivers attempt to pass while I am signaling a turn. This needs a lot of traffic observation."* [P6] and *"Danger of overlooking a car or distorting the handlebars"* [P5]. However, three participants did not experience cars approaching from behind and felt relatively safe.

5.7.3 Scenario D: Left turn at uncontrolled intersections. For this scenario, the participants mentioned the lack of traffic to stress them, easy decision-making process as there were fewer factors to think about, and the advantage of narrow streets, so that cars could not overtake them while waiting to cross. As some of them commented *"not much traffic, a common scenario, no difficult turns"* [P1], *"Not difficult when there is no traffic, a little more difficult when there is traffic."*[P3], and *"There were no cars coming in that direction and if they were then they had to wait for me."* [P8].

6 DISCUSSION AND FUTURE WORK

Our results show that head rotation frequency and duration and not the size of rotations indicate perceived cyclists' safety. The higher the frequency and duration of head rotations, the lower the feeling of safety. These correlations apply to all four situations explored indoors and one (turning left at uncontrolled intersections) outdoors. Moreover, our proposed approach employed outdoors has the potential to create a crowdsourced risk assessment of cycling routes. We discuss these findings in the following subsections.

6.1 Perceived Safety and Head Movements

As discussed, perceived cyclists' safety is reflected via head rotation frequency and duration. The outdoor results confirm our indoor findings but only for one situation – turning left at uncontrolled intersections. We see multiple reasons for this difference. Firstly, indoor and outdoor cycling experiences are different, given that cyclists are more used to cycling outdoors than indoors and might have a higher feeling of confidence and familiarity with traffic situations, as reflected in the qualitative feedback. Secondly, cycling indoors is predictable and predetermined by the virtual environment, while cycling outdoors is "noisy" and introduces many uncontrolled situations. For example, we created an outdoor route that included streets with many parked cars. Still, due to the lack of traffic outside of rush hour, all the participants cycled in the middle of the road without overtaking parked cars, which resulted in the exclusion of scenario B from our data analysis. For safety reasons, we purposefully decided to conduct the outdoor experiment outside of rush hours, while in the indoor simulator, participants experienced a busy traffic flow. Thirdly, we conducted our experiment in a European city with a well-developed cycling infrastructure that facilitates a safe feeling for cyclists and higher awareness of them from other road users, especially car drivers. Therefore, future work should explore busier and more controlled traffic scenarios outdoors that would increase their head rotations.

As for the size of head rotations, we discovered that it does not correlate with perceived safety, given that some situations require certain behaviors, such as shoulder look, that lead to a rotation angle larger than 90° but does not necessarily lead to a high frequency or duration. However, the head rotation angle for lane changing for turning left did not lead to angles larger than 90° unlike overtaking an obstacle on obstructed lanes that resulted at 124°. We assume that cyclists changed lanes in advance rather than at the intersections where we measured their behavior. This temporal aspect of cyclists' head movements is another interesting line of research that needs further investigation, such as when the head turns should be measured, how big the timeframe should be, and what they mean at specific times and traffic situations. We also found that perceived cyclists' safety was rated higher outdoors than indoors. This is likely due to the lack of traffic and greater familiarity with bicycling outdoors than indoors. However, we observed that outdoor cyclists turned their heads to the right more than indoor cyclists. This can be explained by the fact that cyclists are more likely to pay attention to traffic coming from the left and right in real traffic than in a simulation. We also explored situation detection from our data, as our approach can extract different types of interactions. Our results show that shoulder glances, overtaking, and checking traffic before turning left are all possible actions we can detect on the road. Therefore, future work should explore more sensor data to expand the situations that can be detected.

6.2 Quantifying head movements

Since studying human activity involves understanding head motion [8, 48], we employed widely available off-the-shelf hardware and investigated its capabilities under real-world conditions. We extracted and differentiated head movements using the 360° video as a ground truth. The setup was reliable, and participants reported no problems using headphones while cycling. Since the setup needs no initial calibration, it can be suitable for unsupervised crowdsourcing in future work. Due to its reliance on widespread hardware, we envision the usage in decentralized larger applications utilizing privately owned hardware. However, the setup might require further improvements. One is related to the drift of the angles over time that can be addressed via additional magnetometer corrections, as discussed by previous work [9, 13]. However, more approaches need further exploration in the future, e.g., eye tracking to track the movement of the eyes to provide information about the head's movement concerning visual stimuli. Additionally, future work might need to explore head motion capture that involves using cameras and sensors to track the movement of markers placed on the head to create a 3D model of the head's movement. Our results show initial findings based on the proposed minimalistic approach and provide a better understanding of quantifying cyclists' perceived safety. Similarly to previous work, it can also be employed for augmenting helmets with Inertial Measurement Units to detect head movements and improve the recognition rate [3, 14, 16] and sending rescue requests and prevent accidents [4].

6.3 Virtual Reality vs. Outdoors

We discovered the participants' differences in perception and behavior between virtual reality and the outdoors. Cyclists perceive some cycling scenarios as less complicated or with comparable difficulty outdoors, e.g., lane changing and turning left at uncontrolled intersections, than in the VR bicycle simulator. Although VR bicycle simulators are designed to replicate cycling in safe indoor conditions, simulation most likely restricts cyclists' perception of the environment necessary to decide on traffic. Moreover, the VR bicycle simulator lacks realism and might be a novel experience, unlike the outdoors that cyclists are used to. The field of view (FoV) influenced the cycling perception of traffic, given that the Vive Index has a reported FoV of 130°, which is smaller than >180°of the human eyes. This has likely affected head rotations since moving eyes side-wise allows for increased visibility without head movement, which is impossible in VR due to the flat display in front of the eyes. Another explanation could be higher confidence and more experience cycling outdoors than in a simulator. This brings us to the conclusion that bicycle simulators require a higher level of realism that places a technical challenge. Although outdoor evaluations can be dangerous, they provide considerably different results from indoors. Lastly, detection of the head movements could be improved using machine learning analysis of the time series [8, 13, 44, 47], which should be explored in future work.

7 LIMITATIONS

Outdoors, we observed a drift over time resulting from the lack of a magnetometer. We tried a straightforward approach by calculating the mean value for a defined timeframe of 60 seconds, using it as the baseline value to extract movements and angles. AirPods Max could yield more accurate results, as they come with a built-in magnetometer. Given the focus on head movements, we excluded other methods for understanding cyclists' behavior and physiological data, e.g., ECG and EEG. However, with our findings, we step toward understanding cyclists' perceived safety. Our proposed approach was verified using the data from the video observations. It would require a comparison with other established methods to understand its limitations and precision of measurements. The outdoor evaluation included eight participants; more participants are needed for future evaluations. However, with this work, we initially explored head movements to quantify cyclists' perceived safety. Lastly, participants indicated their safety after a ride, which can potentially introduce recall bias. Thus, including a real-time safety self-report can improve this aspect.

8 CONCLUSION

We investigated the quantification of perceived cyclists' safety by head rotation in virtual reality and outdoors. Our results from the indoor experiment suggest that the frequency and duration of head rotation, rather than the rotation angle, reflect cyclists' perceived safety. Using our approach based on Apple AirPods and an iPhone attached to a bicycle outdoors, we confirmed the indoor results that perceived safety correlates with the frequency and duration of head rotation, but only at uncontrolled intersections when turning left. Thus, the frequency and duration of head turn, rather than angles, reflect the perceived safety of cyclists in specific traffic situations, and our approach can facilitate risk assessment of bicycle lanes.

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