Invisible Hazards Made Visible: Augmented Warnings for Urban Cyclists

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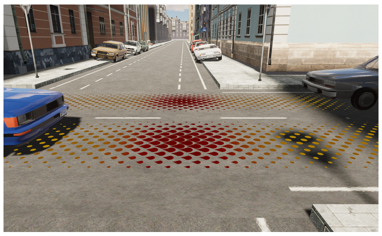

Fig. 1. We propose an AR concept to visualize hazardous areas for cyclists. As depicted for an intersection, such zones are encoded as teardrop-shaped tiles pointing toward the source of danger, while color intensity gradually signals risk level. The system adapts dynamically using direction of travel while riding, or gaze direction when standing.

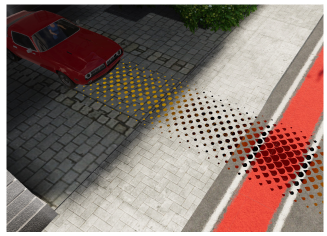

Fig. 2. Highlighting the hazardous area caused by a vehicle exiting a driveway. The red color indicates a high level of danger. The teardrop-shaped tiles point towards the source of the danger (the car).

Fig. 3. Hardware setup of the bicycle simulator consisting of an ordinary bicycle where the rear wheel is replaced by a bike trainer. The cyclist wears VR glasses (not shown) to experience the virtual world.

Cyclist fatalities in Europe have decreased by only 3.0% since 2012, compared to a 22.0% decline in overall traffic deaths. As cycling gains importance as a sustainable mode of transportation, improving cyclist safety is essential. Augmented Reality provides opportunities for effective warning systems through spatial anchoring, embedding information in the real environment rather than fixing it at a static point in the field of view. Although prior work has focused on highlighting specific *Hazardous Objects* themselves, the spatial visualization of *Hazardous Areas* around them remains underexplored.

This paper introduces a concept to visualize *Hazardous Areas* for cyclists, which we designed using a human-centered design approach and which we evaluated in a within-subject simulator study ($n = 17$). Results indicate that the visualization increases subjective safety, lowers perceived workload, and achieves high usability and user experience. Importantly, it enables hazard perception beyond the direct line of sight, addressing key limitations of prior visual warning systems.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI)**; **User studies**; **Empirical studies in HCI**; **Mixed / augmented reality**.

Additional Key Words and Phrases: Augmented Reality (AR), Cyclist Warning Systems, Cyclist Safety, Hazard Awareness, Simulator Study, Sustainable Mobility

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1 Introduction

Road safety for vulnerable users remains a global challenge, with cyclists being particularly at risk. In the European Union, cyclist fatalities have decreased by only 3% since 2012, compared to a 22% reduction in overall traffic fatalities [5]. This disparity highlights that cyclists benefit less from existing safety measures, especially in dense urban environments. Improving their safety is therefore crucial for both public health and sustainable mobility.

Augmented Reality (AR) has emerged as a promising technology in this context, enabling warnings to be displayed directly within the rider's field of view [24, 25]. A key advantage of AR lies in its spatial anchoring of information, which allows hazards to be perceived without diverting attention from the road. According to Wang et al. [26], AR-based hazard visualizations can be grouped into two categories: object-based warnings (e.g., highlighting vehicles) and area/trajectory-based warnings. While existing work has primarily focused on the former [6, 15], the effects of area-based visualizations remain underexplored.

Moreover, most AR warning systems address narrowly defined scenarios, such as intersections [15], dooring [24], or static hazards [30]. Accident statistics, however, show that a wide range of situations contribute significantly to crashes, e. g., errors when merging into traffic account for 12.1% of bicycle accidents in Berlin [18]. This underlines the need for more generalizable warning concepts.

This work addresses these research gaps by introducing and evaluating a novel visualization approach that highlights *Hazardous Areas* instead of isolated objects. Unlike scenario-specific systems, this approach is context-independent and designed to cover both static and dynamic hazards. We compare this approach against object-based warnings and a no-visualization baseline to examine its impact on cyclists. Furthermore, highlighting *Hazardous Areas* may increase the acceptance of visual warnings, which are often considered less effective than auditory or haptic signals due to issues of distraction, comprehensibility, and visibility [10].

1.1 Contribution Statement

In this work, we a) present a user-centered development of an AR concept for visualizing hazardous areas for cyclists, which we b) evaluated through a simulator study. To complement the concept, we c) provide a catalog of potential hazard areas and d) recommendations that can influence future designs and research. Framed in terms of HCI contributions, this work constitutes both an empirical study and an artifact, following the classification by Wobbrock and Kientz [28].

2 Background & Related Work

Several studies have explored the use of AR to improve cyclist safety. This section reviews related work on cyclist-oriented systems, followed by research on hazard visualization in the automotive domain. As we focus on user interfaces for cyclists, we only present studies focusing on presentation and user aspects. For broader overviews on assistance and warning systems including sensing and communication, we refer to Kapousizis et al. [11] and Jannah et al. [10].

Kapousizis et al. [11] provide a comprehensive survey of existing assistance systems and propose a six-level taxonomy of bicycle smartness levels (BSL), which we use in this chapter to classify prior work. Level 0 represents conventional bicycles and e-bikes without smart features, while Level 5 envisions an intervention ecosystem in which traffic authorities actively influence operations in real time, for example by automatically adjusting speed at critical locations.

2.1 Assistance Systems for Cyclists

Cyclist assistance systems include technologies that provide passive support through information delivery, they are classified as BSL level 1 [11]. Common examples comprise accident detection systems, which automatically send emergency notifications when a crash is detected [9], aiming to reduce the critical time between an accident and medical treatment. Navigation systems represent another major category, designed to guide cyclists along safer routes. Unlike general-purpose services (such as Google or Apple Maps), these approaches emphasize traffic safety aspects [11], for example, by providing visual cues directly on the handlebar to reduce smartphone use while riding [7]. Wang et al. [27] have investigated typical car assistance systems, such as adaptive cruise control, on bicycles and tested them in a VR environment.

2.2 Warning Systems for Cyclists

In this paper, we define warning systems as systems that actively alert cyclists to potential hazards, for example, through visual or auditory signals. They correspond to BSL Level 2. This section reviews existing work focusing on user-oriented hazard visualization. We start with a general overview, followed by studies specifically addressing visual signals in AR.

2.2.1 Overview. Many studies aim to improve traffic safety through the development of warning systems. Jannah et al. [10] provide a comprehensive overview and classify warning triggers into three categories:

- *Nearby traffic* — e. g., alerts triggered when other road users approach with a low Time To Collision (TTC) [29].
- *Stationary obstacles* — such as parked cars [24] or potholes [1].
- *Riding behavior* — e. g., excessive speed [13].

Most existing systems focus on traffic-related hazards in specific scenarios, such as dooring [24] or uncontrolled intersections [15], while only few systems spanning multiple categories [10].

In terms of modalities, Jannah et al. [10] report that auditory signals are generally preferred, with some studies also showing strong support for vibrotactile feedback, although real-world vibrations may interfere with its effectiveness. Visual warnings are less favored, mainly due to distraction, lower comprehensibility, longer perception time, and the possibility of being overlooked if the cyclist looks away.

Research on multimodal systems suggests that combining modalities can mitigate such drawbacks and often outperforms unimodal approaches, for instance by reducing cyclists' reaction times [14, 22]. Nonetheless, this work focuses on a purely visual warning system to allow comparison with other visual approaches, while specifically addressing the known limitations of visual warnings without relying on multimodality.

2.2.2 Visual Warning Systems in AR. Matviienko et al. [15] investigated the effects of AR visualizations on cyclists' decision-making at uncontrolled intersections. The study compared two different AR concepts:

- *X-Ray* — a visualization that reveals occluded vehicles through an x-ray-like view.
- *Countdown* — a visualization that displays the remaining time until a vehicle arrives at the intersection.

The results showed that the *X-Ray* visualization enabled faster gap selection between vehicles and reduced mental workload, while the *Countdown* visualization provided a stronger sense of safety and a better overview of the intersection.

Zhao et al. [30] introduced a concept called "HazARdSnap" for delivering information to cyclists. They designed an algorithm that detects hazards and anchors relevant information directly to them once they are looked at. Both "HazARdSnap" and a simple forward-facing AR interface supported cyclists in reading information without looking down. This resulted in a reduction of collisions with virtual obstacles by 51% and 43% compared to a smartphone interface [30]. Overall, these findings indicate that *HazARdSnap* and similar AR-based information delivery concepts have strong potential to enhance cyclist safety by presenting information in a way that does not divert attention away from the road.

Von Sawitzky et al. [24] proposed a system that informs cyclists about potential dooring hazards when approaching parked vehicles using Awarness Messages (AM). Their study employed a bicycle simulator in a VR environment, where visual AMs were displayed at a fixed position in the center of the screen. Participants experienced four conditions: a baseline without AMs, visual AMs, visual AMs with auditory cues, and visual AM with spoken messages. Results showed that while participants did not reduce their speed, they increased their lateral distance from parked vehicles, thereby maintaining safer clearance. This indicates that AM raised participants' awareness of potential hazards and improved their safety behavior.

In a later study, Von Sawitzky et al. [25] conducted a focus group that generated several design concepts for hazard visualization, including:

- *World-fixed Hazard Overlays* — hazards are anchored in the environment, with *Hazardous Objects* highlighted in red and trajectories displayed using arrows.
- *Hazard Overlays and "Blurred Future"* — hazards are represented by predictive visualizations of possible future states.
- *Smart Simplicity* — hazards are displayed at fixed positions close to the scene of interest.
- *Hazard Indication through Icons, Target Points and Screen Edge Utilization* — hazards are shown via icons with distance indicators; if the object is outside the field of view, icons appear at the corresponding screen edge.

The concept most closely related to this work is "World-fixed Hazard Overlays", which combines object highlighting with trajectory visualization. However, it does not generalize *Hazardous Areas*, nor has it yet been implemented or evaluated in a user study.

2.3 Visualizing Danger in the Automotive Context

Wang et al. [26] examined the effects of AR projections on driving behavior and safety. They proposed two types of spatially anchored visualizations of hazards:

- *Visualization of hazardous objects* — Virtual Wall: stacked vertical blocks behind a Hazardous object, with wall height indicating risk level.
- *Visualization of hazardous areas/ trajectories* — Red Carpet: a red rectangle-shaped surface with raised edges extending behind the object, with length encoding risk.

Their study showed that participants using the Red Carpet design maintained safer headways compared to those without AR support. However, no significant differences were found in braking reaction time, maximum deceleration, or minimum TTC. Mental workload was also unaffected. These findings highlight the potential of area-based hazard visualization in the automotive context. The authors recommend reducing the frequency of critical events and using random assignment in future studies to avoid order effects — suggestions incorporated into this work's user study.

Colley et al. [4] investigated how visualizing uncertain trajectory predictions in highly automated vehicles affects trust, situation awareness, and cognitive load. Two visualization strategies were tested:

- *Own planned trajectory* — a line showing the automated vehicle's intended path.
- *Predicted trajectories of other road users* — lines indicating predicted movements of surrounding vehicles.

Results from two online studies showed that color gradients (blue = high certainty, red = low certainty) most effectively conveyed prediction uncertainty. Visualizing the vehicle's own trajectory increased trust, while visualizing others' trajectories improved perceived safety. No significant differences were found in cognitive workload, but combining both visualization types enhanced perceptions of vehicle control and maneuver planning. These findings suggest that trajectory-based visualizations, especially when enriched with uncertainty cues, offer clear benefits. Such approaches could also be applied to cyclist safety, as many hazards emerge along the trajectories of surrounding vehicles.

In the field of motorcycle assistance systems, Savino et al. [19] have found that acoustic and visual HMIs are best suited for "understanding the warning content." Subsequently, they developed design guidelines for voice interfaces for cyclists[20]. In the field of vision assistance, HUDs are one of the technologies that can be used on both motorized two-wheeled vehicles and bicycles.

2.4 Bicycle Simulators

Bicycle simulators are widely used in research on warning systems, as they allow the safe testing of hazardous scenarios within a fully controllable environment [10] before conducting experiments on real roads. Nevertheless, the user behavior in simulators can only partially transferred to real-world contexts. Key reasons include the absence of physical interactions such as inertial forces and tilts [16], reduced immersion, and restricted action possibilities depending on the specific setup [10].

A notable implementation is the simulator by Ullmann et al. [23], combining a physical bicycle with VR. It employs a Hall sensor for speed measurement, a device for steering input, and binaural spatial audio to enhance immersion, while dynamic traffic is simulated through a Unity-based environment. The speed measurement approach is particularly relevant here, as inaccuracies in this area can reduce immersion and contribute to simulator sickness.

Simulator sickness remains a major challenge in VR. Matviienko et al. [16] show that steering with a physical handlebar results in fewer symptoms than methods based on head or torso movements. They also identify artificial airflow as an effective countermeasure, which both alleviates symptoms and increases realism by simulating headwind.

2.5 Research Gap

Based on the theoretical considerations by Wang et al. [26] we identified the analysis of visualization of *Hazardous Areas* beyond specific scenarios such as dooring as a research gap in bicycle warning systems. In our work, danger is not limited to individual objects but conceived as a spatial property that may extend continuously across the environment. Such visualizations allow the extent and intensity of risk to be conveyed, supporting the communication of complex or dynamic situations such as moving vehicles or complex intersections.

For the initial study reported in this paper, we focused on visual assistance to enable a controlled evaluation of the core concept and establish a clear baseline before investigating potential multimodal extensions.

3 Concept

This work investigates the potential of AR visualizations of *Hazardous Areas* for improving cyclist safety. While prior work on highlighting *Hazardous Objects* such as vehicles or static obstacle is seffective in some cases, this approach is limited to objects within the direct line of sight and may not adequately support cyclists in perceiving broader danger zones (e.g., cross traffic at intersections). Our concept seeks to address this gap by visualizing areas of elevated risk, dynamically anchored to the riding or gaze direction of cyclists.

3.1 Research Questions and Hypotheses

To evaluate this approach, we structured our research around one overarching research question RQ1 and two sub-questions (RQ1a, RQ1b):

RQ1 How does the visualization of *Hazardous Areas* affect cyclists compared to *Hazardous Object* visualizations and a non-augmented ride?

- **RQ1a** How does the visualization of *Hazardous Areas* influence cyclists' objective riding behavior?
- **RQ1b** How does the visualization of *Hazardous Areas* affect cyclists' subjective perceptions (e.g., safety, workload) and acceptance?

To answer our research questions, we combined confirmatory and exploratory approaches. For RQ1b we derived explicit hypotheses based on prior work. In contrast, we exploratively investigated RQ1a to capture additional user perceptions and uncover patterns beyond initial assumptions. This design allowed us to validate expected effects while also gaining a broader understanding of how cyclists interact with the visualization.

H1 The visualization of hazardous areas **increases subjective safety** in traffic compared to highlighting Hazardous Objects or providing no warning system.

Since *Hazardous Areas* convey more relevant information about potential hazards, it is expected that users' perceived safety increases. The ability to detect danger early can also strengthen trust in the warning system. This effect has been observed in related studies [10, 15, 24].

H2 The visualization of hazardous areas **does not increase subjective workload** compared to highlighting hazardous objects or providing no warning system.

Although more information is presented, the system is designed to deliver it intuitively and clearly, minimizing additional cognitive load. Several studies support this hypothesis [10, 21, 24], with some even reporting a reduction in subjective workload [6, 15]. A conservative hypothesis is chosen due to concerns about potential information overload expressed during the design process.

H3 The visualization of hazardous areas provides a **similar usability** as the visualization of hazardous objects.

Both visualizations (of hazardous areas and objects) were developed user-centered and iteratively optimized, and are therefore expected to offer comparable usability.

H4 The visualization of hazardous areas provides **similar user experience** as the visualization of hazardous objects.

The reasoning for Hypothesis H3 also applies here; user experience is expected to be similarly positive. An assistance system is supposed to protect the user from hazards; however, it will only be utilized if it is easy to operate and user-friendly. That is why we measure these usability and the user experience.

3.2 User-Centered Development

In order to adapt the car-based concept developed by Wang et al. [26] to cyclists, we carried out the process shown in Figure 4. Our focus was on user-centered design and functionality. The process began with a focus group, proceeding through hypothesis formulation, study-procedure definition, simulator software creation, hardware adjustments, and ended with conducting the user study.

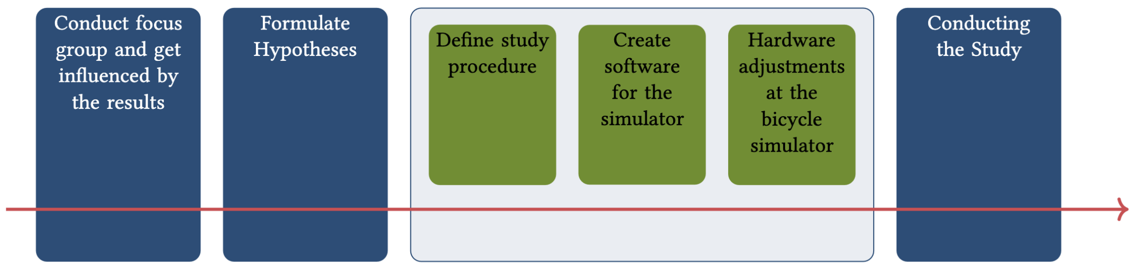

Fig. 4. Schematic representation of the concept of user-centered development of AR assistance for cyclists.

The Red Carpet design proposed by Wang et al. [26] used by car drivers differs substantially from the approach presented in this chapter. While the former projects a red, semi-transparent rectangle behind cars, our work adapts the concept to cycling and develops a user-centered representation with multiple warning levels. By integrating trajectories and static hazards, the visualization is generalized to all forms of risk and aims to overcome central limitations of existing visual warning systems.

3.3 Infrastructure Requirements

The increasing connectivity of vehicles enables new opportunities to improve cyclist safety through warning systems. Both systems implemented in this work rely on information exchange via Vehicle-to-Everything (V2X) technologies [17]. While the required data may include position, type, occupancy, and speed of vehicles, the central question of this work (how different visualizations affect users) can be addressed largely independently of data availability.

The underlying concept considers danger as a continuous, spatio-temporal property influenced by the environment and the behavior of other road users. This allows risk to be visualized either volumetrically or projected onto a surface.

3.4 Formative Insights

To initiate the user-centered concept development and design of risk-area visualizations, we conducted a focus group.

3.4.1 Participants. We recruited participants via an internal university mailing list and invited four male participants, (3 students, 1 employee; 1 participant uses a bicycle several times per week, the others use it almost daily). Three participants were aged 18–24 years, and one was aged 25–34 years. Three participants held a secondary school diploma as their highest qualification, while one held a master's degree. All participants reported living primarily in an urban area and agreed that they were open to new technologies.

3.4.2 Procedure. The focus group lasted approximately 60 minutes. The first half was dedicated to gathering general insights, while the second half focused on a deeper exploration of the topic. After a short introduction and consent procedure, participants were asked to describe situations they considered most hazardous, followed by a brainstorming of additional hazardous scenarios. The discussion then shifted to possible ways of addressing such dangers through AR warnings and to desirable characteristics of AR visualizations. In the second half, each participant developed and sketched their own concept for visualizing *Hazardous Areas* using example images, before presenting and discussing their proposals. The session concluded with a group discussion aimed at comparing design aspects (e. g., color) and reaching consensus on key elements.

3.4.3 General Results. The participants discussed general experiences and ideas. They reported a variety of hazardous situations encountered in cycling, including conflicts at intersections (e.g., poor visibility of side streets, risky overtaking while turning), close or unsafe overtaking maneuvers, “dooring” incidents (vehicles parked at the side of the road suddenly open their doors), abruptly ending bike lanes, sudden obstacles such as pedestrians, animals, or barriers, and adverse weather conditions.

Participant suggested concepts or AR-based warning systems included highlighting *Hazardous Areas* or objects, displaying warning texts or symbols, providing action recommendations (e.g., “Brake!”), integrating warnings into navigation systems, alerting to hazards outside the field of view, and visualizing the safest route.

The participants identified several desirable properties of AR visualizations for the subsequent design process. These included seamless integration into the environment to avoid distraction, high intuitiveness and rapid interpretability, clear visibility under varying conditions, the ability to represent out-of-view hazards, minimal cognitive load, and adaptive information presentation.

3.4.4 Design Development. The participants developed their own design ideas and attempted to establish consensus on how *Hazardous Areas* should be highlighted. Some expressed concerns that large filled surfaces might be overwhelming and obscure relevant information; warnings should therefore be as noticeable as necessary but as subtle as possible. The group rejected highlighting safe or optimal areas, as this could create legal and ethical issues and foster a false sense of security in case of technical errors. Similarly, informing users about recognized but harmless situations was dismissed, since it could overload users and reduce sensitivity to actual dangers.

To address adaptivity and minimize cognitive load, participants suggested introducing three warning levels: (1) hazards requiring increased attention (e.g., a truck’s blind spots), indicated with sparse markings; (2) hazards requiring active reaction (e.g., dooring), shown with denser markings and a filled border; and (3) hazards requiring immediate response (e.g., vehicles failing to yield), represented by fully filled areas.

Color choice was extensively debated. While red is a common warning color, its effectiveness may be reduced as many bike lanes in the authors’ country are colored in red already. Alternatives such as black or context-sensitive approaches were discussed, but black was dismissed due to poor visibility in darkness. The most promising idea was to adapt the visualization to the local background (for example, by inverting, brightening, or desaturating it) to ensure consistent visibility while preserving environmental details. This approach is pursued further in our design.

3.5 Hazardous Situations

We selected several scenarios for detailed analysis and to compare the warning systems. To minimize complexity, we focused on only two of the three hazardous situations identified by the focus group. These were chosen because participants highlighted them as particularly relevant or because they appeared in existing literature.

All situations were designed so that recognition and avoidance would be possible even without a warning system, so that a) a baseline is possible and b) the situations appear realistic (i.e., solvable). For example, every vehicle causing danger was occupied by a visible driver, allowing participants to assess potential risks. The specific scenarios are described below along with their rationale. All distances and times were discussed in the focus group or correspond to the authors' experiences in road traffic.

(a) *Dooring:* Vehicles are parked along the roadside and sidewalk. One vehicle door opens for $5.0s$ once the cyclist is closer than $15.0m$. This scenario was frequently mentioned in the focus group and considered in related work [24].
(b) *Unregulated intersections:* The cyclist must cross a busy priority road with traffic crossing at $50.0km/h$. This situation has been widely studied in related work [6, 14, 15].
(c) *Driveway exits:* A car pulls into the road across the bike lane without yielding, starting at $13.0m$ distance and accelerating to $30.0km/h$. This scenario was emphasized in the focus group and represents a larger group of accident reasons (e.g., 12.1% of accidents in Berlin [18]).
(d) *Right-turn conflicts:* A car overtakes and immediately turns right, cutting in $4.0m$ ahead at $14.4–43.2, km/h$. This scenario is a common cause of accidents (e.g., 50.6% of all bicycle accidents in Berlin [18]).
(e) *Oncoming traffic:* Vehicles in the opposite lane prevent cyclists from freely evading hazards.

In the dooring and failure-to-yield scenarios, drivers might also react correctly by waiting or stopping. Since warning systems cannot be expected to predict this perfectly, *false positives* of these situations are also examined. They are visualized in the same way as actual hazards.

4 Implementation

In order to evaluate the proposed concepts in a safe environment and due to the lack of real-time information about all road users and vehicles around the cyclist, we decided to test our concepts in a cycling simulator.

4.1 Hardware: Bicycle Simulator

The simulation environment is based on a stationary, static bicycle simulator, consisting of an ordinary mountain bike used in combination with a Tacx NEO 2[1] for pedaling and an Elite Sterzo Smart[2] platform for steering as shown in Figure 3. The cyclist experiences the environment through a VR headset (Varjo Aero[3]).

The Tacx NEO 2 only provides speed updates at $1.0\ Hz$ causing noticeable delays during acceleration. To improve responsiveness we measure the user's pedaling behavior externally at a higher frequency: Inspired by Ullmann et al. [23], where Hall-effect sensors on the rear wheel were used, we implemented an optical tracking approach. A printed tachometer with 36 alternating black and white sectors was attached to the flywheel, providing an angular resolution of 10°, which has more than tripled the sampling rate. Transitions are sampled at $1000.0Hz$ by an an optical reflection sensor (TCRT5000). This allows detection of all realistic cyclist speeds, with a theoretical maximum of $v \approx 43.0\mathrm{m/s}(155.0\mathrm{km/h})$.

4.2 Software: Bicycle Simulator

The simulation itself was implemented using the Unity *2022.3.52f1 LTS* game engine. Appendix A.1 provides an overview of all assets used to create the visual content of the virtual environment.

[1] https://www.garmin.com/p/690886/, last access: 2025-09-09
[2] https://www.elite-it.com/en/products/home-trainers/ecosystem-accessories/sterzo-smart, last access: 2025-09-09
[3] https://varjo.com/products/aero/, last access 09-11-2025

Fig. 5. Map of the route with all possible locations of hazardous situations. The circle at the end of a line is the starting point for vehicles, while the other end is the end point. Lines without circles symbolise areas where hazards may occur.

4.2.1 Driving Route. The simulated environment consisted of a road network with intersections whereby the participants had to drive a distance of approx. 1 *km*. Roads were about 7 *m* wide with a 10 *cm* curb, modeled and textured based on a road asset package. Three road types were included: two-lane roads, two-lane roads with bicycle lanes, and one-way streets with a single bike path.

As shown in Figure 5, participants started at the top-left corner and cycled straight through each intersection until reaching the goal at the top right. Hazardous situations were embedded along the route and are color-coded on the map.

All streets were surrounded by buildings, trees and other decorative elements to create a realistic environment. Some hazards, such as driveways, were intentionally partially concealed. Care was taken to keep the scenery diverse, with assets rarely reused. A complete list of assets is provided in the appendix.

The route included a total of eight hazardous situations: 2 instances of dooring, 2 unregulated intersections, 1 case of failure to yield at a driveway, 1 right-turn conflict, and 2 encounters with oncoming traffic. False positives were excluded and are described in the following section.

To avoid habituation effects without compromising the comparability of the results, the appearance and position of vehicles were randomized. In addition false positives were also inserted in the dooring areas so that the same vehicle did not always open its door.

4.2.2 Audio. For audio playback, Unity's built-in spatial audio system was used.

4.2.3 Traffic. The simulation of moving traffic is based on the path planning and is applied in the *Unregulated Intersection* and *Oncoming Traffic* scenarios. Vehicles are spawned at fixed locations and move toward predefined destinations. Each

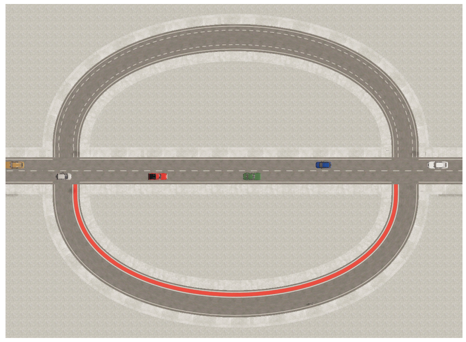

Fig. 6. Training track used in the user study for familiarization.

vehicle is randomly assigned one of eight available models (see Appendix A.1) and a random color to create realistic visual diversity. Traffic flows are modeled using queuing theory: the distance between consecutive vehicles follows an exponential distribution, with defined minimum and maximum bounds to prevent collisions or sparse traffic. To ensure reproducibility, the random seed is based on the XZ coordinates of the spawn location, maintaining realistic yet consistent traffic behavior.

4.2.4 Handling of Accidents. All vehicles in Unity are assigned capsule-shaped collision zones. Accidents are defined as the intersection of the cyclists and such a zone. In this event, the vehicle is deleted and a car-horn sound is played. Collisions are communicated only acoustically to avoid discomfort or ethical concerns.

4.2.5 Training Track. The training track used for familiarization with the simulator consisted of an elliptical road intersected by a straight main road (see Figure 6). Cars traveled along the main road, creating two unregulated intersections. Participants were instructed to ride along the elliptical road, half of which featured a bike lane and the other half a cycle advisory lane, allowing them to practice natural and safe cycling within narrow boundaries.

4.3 Software: Visualization of the Warning Systems and the Test Track

This subsection explains the implementation of the warning systems according to the design described above.

4.3.1 Colors of the Warning Systems. Both the logic for determining the warning color and the visualization of warnings in the virtual environment build on insights from the focus group. For object highlighting, we drew on prior work by Matviienko et al. [15] and especially Göhler et al. [6]. We tested the designs iteratively and discussed them with several users and experts during development.

The selection of colors for visualizing hazardous elements was guided by focus group insights and designed to adapt dynamically to the local background. This avoids poor visibility of fixed colors and preserves background luminance details, which are particularly important for perception.

This design choice prevents warnings from blending into the background and ensures that they remain noticeable. But importantly, it shows that color alone should not carry critical safety information. The same principle can be applied to accessibility: by simulating color vision deficiencies, similar thresholds can help identify and fix problematic color ranges, making visual warning systems more inclusive and robust.

All warning colors are based on the focus group's recommendations but have been slightly adjusted: The most visually appropriate standardized RAL traffic color (as defined by legislation) was selected. This ensures compliance with current traffic conditions.

4.4 Design of the Warning Systems: Hazardous Areas

Hazardous Areas are represented by a filling of circle- or teardrop-shaped elements (see Figure 7), arranged in a checkerboard pattern virtual fixed in the environment. Risk intensity is conveyed through element size, color, and shape, ensuring accessibility by encoding information beyond color alone. Elements remain static and grow when a hazard approaches, while those left behind shrink to zero. This world-anchored design aims to enhance seamlessness and reduce distraction.

The color adapts automatically, ranging from low to high risk. The highlights gradually fade out beyond a certain distance to avoid overwhelming the user. This approach (showing level of risk by color and origin of hazard by the teardrop-shaped tile) ensures that cyclists can quickly perceive the location, extent, and severity of potential hazards, supporting safer and more intuitive interactions in traffic scenarios.

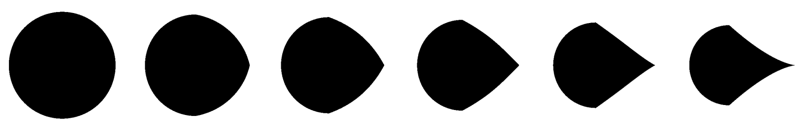

Fig. 7. Modification of the teardrop-shaped tile to highlight the direction from which a hazard is approaching. Left without direction indication, right with reference to the right.

Hazards are divided into two levels, as suggested in the focus group. To reduce information overload, visualizations in level 1 are suppressed in unavoidable everyday risks (e.g., parallel oncoming traffic), and elements gradually fade out beyond $30 - 40\ m$ distance.

(1) *Low risk:* The area requires increased attention. This level uses small yellow circles (see Figure 8).
(2) *High risk:* A concrete accident is imminent. This level employs larger red teardrops pointing towards the *Hazardous Object*, guiding attention first to the area and then to the object itself (see Figure 9).

4.4.1 Display of hazardous situations. The hazard arising by *Dooring* is modeled as elliptically outward from the door. If a person is seated inside a parked car, the area around the door is displayed as low risk. Once the door opens, the entire area escalates to high risk (see Figures 10 and 11). The doors of unoccupied vehicles were not marked as a hazard because we assume that this information can be processed in the V2X context.

The *hazard from moving vehicles* applies to all moving or soon-to-move vehicles, covering all situations except dooring. For simplicity, only two areas are modeled: in front of and behind the vehicle. The front area corresponds to the vehicle's stopping distance. If the cyclist's predicted path overlaps with this zone, it is shown as high risk (level 2). The cyclist's trajectory is estimated from the current steering angle or from head rotation when stationary. The rear area represents the distance needed for the cyclist to match the vehicle's speed. It is displayed only when the cyclist rides faster than the vehicle (e.g., when it is stopped). Both zones fade smoothly at their edges (see Figure 1). Oncoming traffic is treated as low risk only, since it rarely poses an immediate hazard. Dynamic hazards from moving vehicles were visualized as risk zones along their predicted paths. The system emphasized overlaps with the cyclist's expected

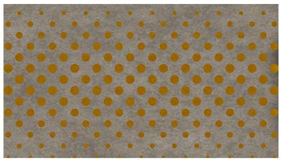

Fig. 8. Visualization of the first warning level (low risk).

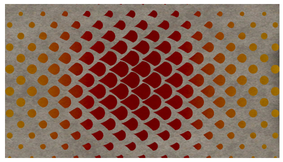

Fig. 9. Visualization of the second warning level (high risk). Here, a car approaches from left.

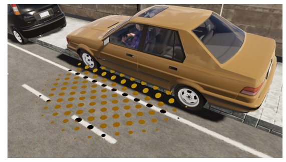

Fig. 10. Danger from closed door that might be opened.

Fig. 11. Danger from an open door.

trajectory, highlighting forward dangers while fading less relevant traffic. This provided timely, context-sensitive cues without overwhelming users with visual clutter.

Hazard from incoming traffic respectively vehicles with occupants parked in driveways are highlighted similarly to moving vehicles. Since the stopping distance is not relevant, the hazard area extends onto the road the vehicle could enter. This behavior is illustrated in Figure 2. Once the vehicle moves, the hazard area updates dynamically as for other moving vehicles.

4.5 Design of the Warning Systems: Hazardous Objects

In this variant of visualization, *Hazardous Objects* are highlighted in the environment, including through walls (since V2X is assumed). They are outlined with a warning color and filled at 25% opacity; windows are excluded to avoid obstructing communication with vehicle occupants. The final color is modulated based on the background.

Two distance-based hazard levels are distinguished, similar to the two levels used for hazardous areas. The distance thresholds were refined through iterative testing to avoid information overload, following principles from Göhler et al. [6]. Highlights are omitted for everyday, unavoidable hazards, such as normal parallel traffic.

(a) *Distant Hazard:* The object is nearby but not in the immediate area. It represents a potential risk that does not require immediate attention. The warning color interpolates from yellow to orange between $60m$ and $15m$.
(b) *Imminent Hazard*: The object is within $15m$ of the user and requires heightened attention. The color is red and the transition from the first level is abrupt to capture attention.

The hazards in the considered scenarios are further categorized in the following subsections.

(a) *Exceptional Hazard* This category includes the situations "Dooring", "Ignoring Right of Way at Driveway", and "Ignoring Right of Way When Turning". In these cases, the *Hazardous Object* is continuously highlighted. The highlight color is distance-dependent, as described earlier, and always visible.
(b) *Ordinary Hazard* This category covers normal traffic, including 'Unregulated Intersection' and "Oncoming Traffic". Here, objects are highlighted only when they pose a concrete risk to the cyclist. Simplifying, this is assumed to occur mainly during turning maneuvers. As shown in Figure 12, the highlight is hidden when the vehicle moves approximately parallel to the cyclist. This behavior is implemented by scaling the opacity of the warning color based on the angle between the cyclist's direction and the object's direction.

Hazardous objects were visualized through a custom rendering pipeline. Potential risks were highlighted in warning colors and remained visible even when occluded. A fullscreen shader generated filled outlines and blended them into the scene, ensuring consistent, perceptible cues that cut through visual clutter.

Fig. 12. Highlighting of normal traffic. The white vehicle that encountered the cyclist is marked with a red frame. Parallel traffic (blue vehicle) is not highlighted.

5 User Study

To evaluate the effectiveness of the warning systems, we conducted a *within-subjects study* to compare the following designs: 1) a baseline condition without warnings, 2) a condition visualizing *Hazardous Areas*, and 3) a condition visualizing *Hazardous Objects*. Each participant completed one ride with each design.

5.1 Procedure

The study procedure is illustrated in Figure 13 and lasted approximately 1 hour per participant. We used a balanced latin square design to control for order effects between the three designs.

First, we introduced participants to the study, explained its procedure and asked to sign the consent form. Afterwards the participants had the chance to get in touch with the bicycle simulator in a (simulated) training track.

The following steps were then carried out for each of the three design variants: The basic principle of visualization was explained, after which the participant was asked to try it out in a test drive. Each design concept was concluded with the completion of several questionnaires (SSQ, TLX, PSQ and if no baseline UEQ-S, SUS).

Once all conditions were completed, the study was concluded with a short ranking, and a semi-structured interview. Participants received a compensation of 15.00 €.

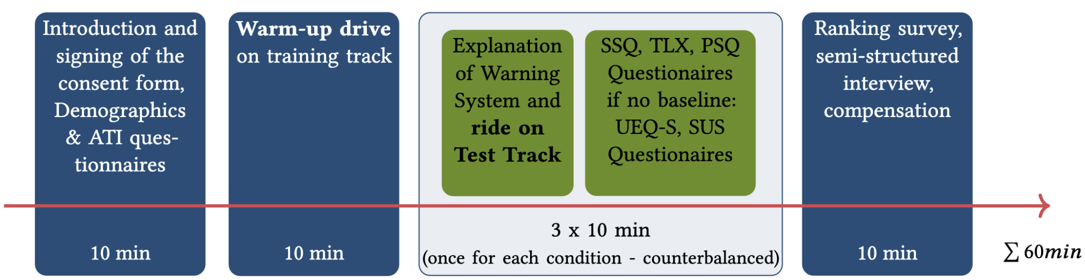

Fig. 13. Schematic representation of the procedure.

5.2 Data Collection and Measures

To address the research questions, we collected a combination of objective, quantitative, and qualitative measures.

5.2.1 Dependent (objective) measurements. To obtain objective insights into participant behavior during the test rides, we record data about user behavior, traffic data and additional statistical data. The specific measurements are shown in Table 1.

	User and Bicycle Data	**Traffic Data**	**Statistical Data**
Frequency	100.0 Hz	50.0 Hz	upon occurrence
Data	• Position, speed and rotation of the bicycle • Dimensions and positions of the collision boundary of the bicycle • Steering angle and force sensor load of front and rear brakes • Signed distance from the road centerline • Distance from the start of the track along the centerline • Position and rotation of the user's head • User's gaze direction and focal distance • Distance to the next fixated object, as well as all cars intersected by the user's gaze ray • Iris and pupil diameter of each eye	• Position, speed, purpose (Dooring, Driving) and rotation of the car • Dimensions and positions of capsule key points used as the collision boundary of the car • Boolean value indicating whether a car door is open • Dimensions and positions of cuboid key points used as the collision boundary of the door • Boolean value indicating whether the car is a false positive	• the user passes the start and end points of the track, of intersections or areas with parked cars • the type of road changes (e.g., from a road with a bike lane to one with a cycle lane marking) • the user collides with a car

Table 1. List of the recorded data for objective measurement divided by three fields: user and bicycle data, traffic data and statistical data.

5.2.2 Quantitative Subjective Data. The following standardized questionnaires were used to record subjective metrics:

- Affinity for Technology Interaction (ATI)
- Simulator Sickness Questionnaire (SSQ)
- NASA Task Load Index (NASA TLX)
- Perceived Safety Questionnaire (PSQ)
- User Experience Questionnaire – Short (UEQ-S)
- System Usability Scale (SUS)

5.2.3 Qualitative Subjective Data. At the end of the study, participants were asked to rank all variants by personal preference and provide a written explanation of their choices. To gain deeper insights, a semi-structured interview was conducted, in which participants could share their impressions and suggestions for improving the warning systems, add general comments on the study and, if applicable, reflect on any accidents that occurred during the rides.

5.3 Ethics

The user study was approved by the ethics committee of the authors' institution under number 2025-07. Participants provided informed consent after being fully briefed about the study's objectives, data handling, potential risks, and their rights. Participation was voluntary and could be withdrawn at any time without justification; compensation was provided regardless of withdrawal. All data were pseudonymized using randomly assigned participant codes.

To minimize psychological strain, collisions in the simulation were deliberately designed in an unrealistic manner: cars honked and disappeared immediately upon impact, without physically affecting the bicycle. Participants were informed beforehand, encouraged to provoke collisions during a familiarization ride, and debriefed in follow-up interviews. Finally, simulator sickness was monitored continuously through observation, targeted questioning, and the Simulator Sickness Questionnaire (SSQ).

5.4 Participants

We recruited 20 participants via the authors' university mailing list, but 3 had to abort due to symptoms of simulator sickness. The remaining 17 participants (12 male, 5 female) completed the study to the end. Ages ranged from 18 to 44 years (M = 23.2 years, SD = 5.8 years). All participants had completed secondary education (equivalent to high school), about one third held a university degree, and roughly five sixths were students. In total, 82% reported cycling at least several times per week, and the same proportion primarily used bicycles in urban environments.

5.5 Representation of Accidents

Overall, there were 27 collisions across all 51 rides — 10 each for *No Visualization* and *Hazardous Objects*, and 7 for *Hazardous Areas*. All 11 participants who experienced a collision were interviewed about the display. They reported that the virtual accidents did not cause any psychological stress or strain. The collisions were perceived as unrealistic, frustrating, and "video game–like", but not distressing.

5.6 Limitations

Despite randomization, the within-subjects design led to learning effects during the study. Several participants reported memorizing the general area of hazards of the route after only one or two runs, allowing them to anticipate and avoid most dangers regardless of visualization, even though they never knew whether a hazard would turn up or not. Although the balanced Latin square likely minimized systematic effects across conditions, driving behavior was overall only marginally influenced by visualization. This observation is consistent with the objective data and may explain the limited number of significant findings, suggesting that these results should be interpreted with caution. It cannot be excluded that the sole knowledge that hazards exist has led to more cautious driving (similar to the time after a near accident).

The use of a simulator further limits ecological validity. Reduced immersion stemmed primarily from missing physical forces and tilts, unrealistic braking dynamics, and the lack of pedal movement. Participants likely also exhibited greater risk tolerance, as no real consequences were involved, potentially affecting driving behavior and thus the generalizability of objective results. Subjective measures, however, are assumed to be less affected.

The entire experiment was carried out in VR, in the full knowledge that any resulting products would be purely AR applications. As no AR glasses of the required standard were available at the time of the experiment, we recreated the entire cycling environment, the bicycle itself and the AR visualisations in VR.

Although the number of participants was sufficiently large, it was not representative of the total population, as most participants were young, academically trained, and highly technology-affine. Older users, who may be more critical toward novel systems, were underrepresented. Nevertheless, no significant correlation was found between technology affinity and subjective ratings, suggesting only a minor influence on the results.

6 Results

This chapter reports the findings of the user study and summarizes the results with respect to the research questions.

6.1 Quantitative Data - Simulator Measurements

In order to answer the research question RQ1a, we statistically analyzed the objective cycling data. We analyzed all data which was presented in the previous section but only report measures that yielded a statistically significant difference.

6.1.1 Deviation of the Head Rotation from Driving Direction. We analyzed the cyclist's head orientation using local Euler rotations (roll, pitch, yaw). The Euclidean norm of these components, called head rotation distance (in degrees), measures deviation from the travel direction. The mean absolute deviation per trial reflects head posture stability, with higher values indicating more frequent or prolonged looking around.

Mean absolute deviations differed across conditions: *Hazardous Areas*: median 132°, mean 131°, SD 44.2°; *Hazardous Objects*: median 143°, mean 141°, SD 48.0°; *No Visualization*: median 152°, mean 142°, SD 46.6°.

As a Shapiro–Wilk test rejected normality ($p = .002$), we applied a Friedman test, revealing a significant difference between conditions ($\chi^2 = 6.1176$, $p = .047$)[4]. Post-hoc Conover tests with Holm correction showed a significant difference between *Hazardous Areas* and *Hazardous Objects* ($p = .045$), while other pairwise comparisons were not significant.

6.1.2 Pupil Diameter. Across the three conditions, we examined the mean pupil diameter. Pupil size was measured in millimeters and averaged over all measurements for each trial. For the *Hazardous Areas* warning system, the median pupil diameter was 5.38*mm* (mean 5.19*mm*, SD 0.99*mm*). The *Hazardous Objects* condition yielded a median of 5.24*mm* (mean 5.18*mm*, SD 0.99*mm*). In the No Visualization condition, the median was 5.39*mm* (mean 5.21*mm*, SD 1.19*mm*).

Larger pupil diameters indicate higher levels of attention [8] and cognitive load [3, 12]. The data were analyzed exploratively, as no hypotheses were pre-registered.

A Shapiro–Wilk test rejected normality of residuals ($p < .001$). Consequently, a Friedman test was applied as an omnibus test, showing a significant difference among conditions ($\chi^2 = 6.1176$, $p = .047$)[4]. Post-hoc Conover pairwise tests with Holm correction revealed a significant difference between *Hazardous Objects* and no visualization ($p = .045$). Differences between *Hazardous Areas* and no visualization ($p = .151$) and between *Hazardous Areas* and *Hazardous Objects* ($p = .468$) were not significant.

As neither mean nor median values suggest a clear ordering between *Hazardous Objects* and no visualization, mean ranks were examined. No visualization (mean rank 27.6) did not show a substantially higher rank than *Hazardous Objects* (24.6), indicating that pupil diameters tend to be larger without visualization. This suggests higher cognitive load and greater attentional demand under the no-visualization condition.

[4]The χ^2 and p-values for "Deviation of Head Rotation" and "Pupil Diameter" are identical. This has been intensively verified on multiple instances. The reason for this is that the Friedman ANOVA procedure is based on ranks. With only 3 conditions and 17 participants, this phenomenon is indeed possible.

6.2 Subjective Data - Evaluation of the Questionnaires

This subsection presents the results of all questionnaires except the Simulator Sickness Questionnaire (SSQ), which we mainly used to assess the participant's current situation.

6.2.1 Affinity for Technology. Participants scored an average of $M = 4.458$ ($SD = 0.681$, $\alpha = 0.804$), indicating an above-average affinity for technology. This measure is later examined for correlations with other metrics.

6.2.2 NASA Task Load Index (NASA-TLX). We administered a NASA TLX after each test drive to capture subjective workload. The results are shown in Table 2.

To formally test equivalence, we conducted two one-sided t-tests (TOST) for paired samples with an equivalence margin of ±6 points (approximately half a standard deviation). For both comparisons (Hazardous Areas vs. *Hazardous Objects* and *Hazardous Areas* vs. No Visualization), equivalence could not be established, as one of the bounds was not significant.

An exploratory repeated-measures ANOVA revealed a significant overall effect of visualization type on workload ($p = .008$, $\eta^2 = 0.141$). Post-hoc tests (Holm-corrected) indicated a significant difference between *Hazardous Areas* and *No Visualization* ($p = .0225$), while the other pairwise comparisons were not significant.

Overall, the equivalence analysis did not provide evidence that the conditions were statistically equivalent. However, the significant reduction in workload for *Hazardous Areas* compared to No Visualization suggests that this visualization may even lower subjective workload relative to baseline. *Hazardous Objects* showed a similar, though non-significant, trend.

Warning System	**Median**	**Mean Value**	**Standard Deviation**
Hazardous Areas	18.33	20.93	13.16
Hazardous Objects	23.33	25.88	13.20
No Visualization	33.33	32.94	11.13

Table 2. NASA-TLX values of the three warning systems.

6.2.3 Perceived Safety Questionaire (PSQ). The PSQ includes five items on a five-point Likert scale, aggregated into a score from 0 to 4. The data of this study is shown in Figures 14 and 15. Repeated-measures ANOVA confirmed a significant effect of condition ($F(1.41, 22.55) = 20.91$, $p < 0.001$, $\eta^2_{\text{ges}} = 0.369$). Residuals were normally distributed (Shapiro–Wilk $p = .346$), and Greenhouse–Geisser correction was applied.

Post-hoc one-sided paired t-tests with Holm correction showed that *Hazardous Areas* scored significantly higher than both *Hazardous Objects* and *No Visualization*, and *Hazardous Objects* also scored significantly higher than *No Visualization*. All comparisons were significant.

6.2.4 User Experience Questionaire - Short (UEQ-S). The UEQ-S consists of eight items on a seven-point Likert scale, aggregated into three scores: pragmatic quality, hedonic quality, and overall score. These standardized scores allow a detailed evaluation of user experience.

The *Hazardous Areas* system achieved an excellent rating for pragmatic quality, placing it among the top 10% of the benchmark, while hedonic quality and overall score were rated as good. In contrast, the *Hazardous Objects* system scored only above average on all three scales, performing worse in mean comparisons (Figure 16 and 17).

Warning System	Median	Mean Value	Standard Deviation
Hazardous Areas	3.00	3.09	0.579
Hazardous Objects	2.80	2.87	0.557
No Visualization	2.00	2.06	0.659

Fig. 14. PSQ values of the three warning systems.

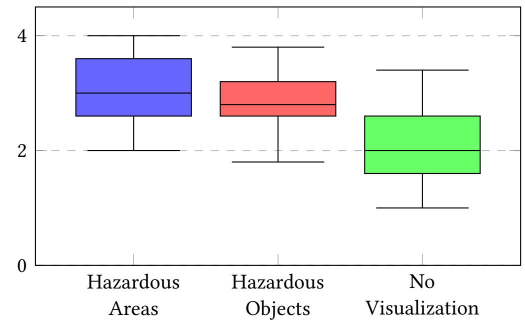

Fig. 15. Visualization of the PSQ values of the three warning systems.

Shapiro–Wilk tests confirmed normality ($p > 0.05$), and equivalence testing using TOST with a ±0.5 equivalence range found no significant equivalence for any scale. Exploratory paired t-tests also revealed no significant differences.

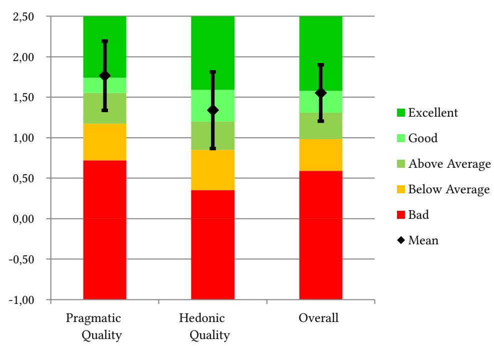

Fig. 16. UEQ-S benchmark for *Hazardous Areas*.

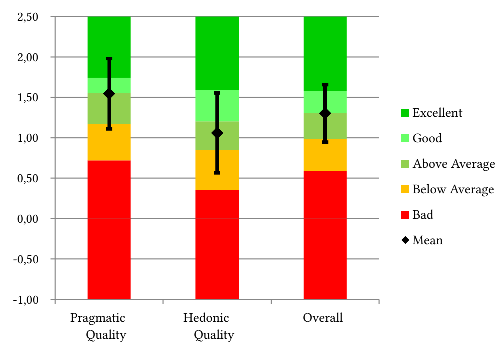

Fig. 17. UEQ-S benchmark for *Hazardous Objects*.

6.2.5 System Usability Scale (SUS). Both *Hazardous Areas* and *Hazardous Objects* concepts had a median SUS score of 82.5. The mean values were 83.68 for *Hazardous Areas* and 83.82 for *Hazardous Objects*, with standard deviations of 11.49 and 10.46, respectively, visualized in Figure 18. These values are considered *acceptable* and rated as *excellent* [2].

Normality was confirmed via Shapiro–Wilk test ($p = .098$), allowing parametric tests. A paired TOST equivalence test with a ±10 point range showed significance for both lower ($p = .007$) and upper bounds ($p = .006$), supporting equivalence. Thus, the SUS scores of the two systems can be considered practically equal.

6.2.6 Ranking. At the end of the study, participants ranked all experienced interfaces by preference. Points were assigned according to rank: first place received 3 points, second 2 points, and third 1 point. Total scores per interface (sum of all participants' points) ranged from 17 to 51 (see Figure 19). The results show that *Hazardous Areas* were generally preferred, followed by *Hazardous Objects*, and finally *No Visualization*.

A Friedman test, suitable for within-subjects ordinal data, revealed a significant difference between the three interfaces ($\chi^2 = 12.118$, $p = .002$). Kendall's $W = 0.357$ indicates moderate agreement among participants. Post-hoc Conover tests with Holm correction showed significant differences between *Hazardous Areas* and *Hazardous Objects* ($p = .022$) and

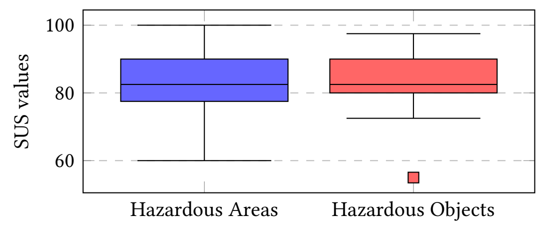

Fig. 18. Comparison of the SUS values for the two warning systems *Hazardous Areas* and *Hazardous Objects*.

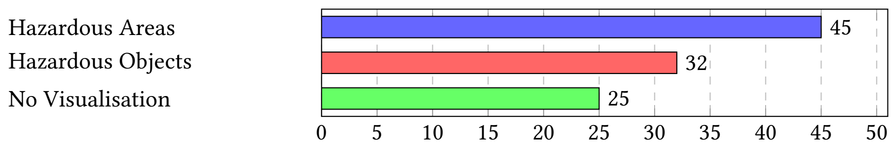

Fig. 19. Summed scores of the ranking for the three interface options *Hazardous Areas*, *Hazardous Objects* and *No Visualization*. The higher the scores, the higher the ranking of the interface among the study participants.

between *Hazardous Areas* and *No Visualization* ($p < .001$), while the difference between *Hazardous Objects* and *No Visualization* was not significant ($p = .156$).

6.3 Qualitative Subjective Data

At the end of the study, we asked the participants using an open-text field to explain their ranking of the three variants. This was followed by a semi-structured interview to capture participants' opinions and experiences. We recorded and transcribed all interviews.

The qualitative results are summarized in this section, with the number of participants making similar comments indicated in brackets.

6.3.1 Reasons for the Ranking. Participants were asked to justify their ranking choices in writing. The responses were summarized and divided into arguments for and against each option.

For the *Hazardous Areas* visualization, participants appreciated its predictive function, which allows early detection of hazards such as braking vehicles or hidden cars (9), as well as the clear localization of dangers, helpful when crossing streets or avoiding suddenly opening doors (3). It also reduced physical effort, as constant head turning was unnecessary (2). However, some participants found the point-and-teardrop design stressful and hard to interpret (2), felt that constantly monitoring the road was distracting (2), and noted increased cognitive load when estimating the speed and direction of *Hazardous Objects* (1).

For *Hazardous Objects*, the simple and intuitive design enabled quick reactions (4), and the "X-ray" view allowed early hazard recognition (2). On the downside, participants reported that continuously searching for markers distracted them from riding (4), that the system provided only limited added value compared to no visualization (2), and that some markers were difficult to see, for example red markings on red cars (2).

With *No Visualization*, participants felt that relying on technical support could be distracting or even Hazardous (2). However, the lack of support in complex scenarios (9), absence of warnings for unseen hazards (4), and the resulting lower sense of safety (3) were seen as major drawbacks.

6.3.2 Suggestions for Improving Warning Systems. In the interview, two open-ended questions were asked about ideas and suggestions for improving the warning systems.

For *Hazardous Areas*, participants suggested improving the directional cues, as the teardrop indicators were hard to see due to blur, distraction, and small size. Larger arrows, color gradients, or an animated "blurred future" showing predicted vehicle movement could enhance clarity (4). A longer warning time was recommended to allow more reaction time, potentially by using more conservative stopping-distance calculations (2). To reduce information overload, participants proposed showing only the most immediate hazards when multiple vehicles are present (2), and using homogeneous, transparent areas with color gradients instead of numerous points and teardrops (1). Additionally, categorizing hazards with different symbols (1) and displaying the areas above the street rather than on it to avoid constant downward glances (1) were suggested.

For *Hazardous Objects*, participants noted that the object outlines were sometimes difficult to see due to low contrast or shadows; higher contrast or additional indicators for objects outside the peripheral view were recommended (4). Red or similarly colored cars were particularly hard to detect, and suggestions included patterned outlines or larger "auras" around vehicles (2). The system was also seen as too distracting, and a subtler presentation was preferred (3). Finally, directional cues for hazards such as overtaking vehicles were unclear and could be improved with arrows or other visual indicators (2).

6.3.3 General Comments. Participants reported a learning effect, quickly becoming familiar with the routes and recognizing recurring hazard situations after only a few runs (3). Some noted issues with immersion, as the braking delay and static pedals in the simulator reduced realism (2). A few participants mentioned reduced attention, feeling that the warning systems took over cognitive tasks, which could increase accident risk in real-world scenarios if false negatives occur; these participants preferred no visualization (2). One participant suggested marking all potential hazards, not just selected objects like occupied parked cars, to provide more comprehensive warnings (1). Finally, the idea of a combined system was proposed to integrate the benefits of both approaches (1).

7 Discussion

This section discusses and interprets the results of the user study. Based on our findings, we subsequently propose recommendations to guide developers and researches when designing future AR warning systems for cyclists.

7.1 Hazardous Area Visualizations Increase (Subjective) Cycling Safety

Our study showed that the PSQ score for *Hazardous Areas* was significantly higher than for *Hazardous Objects* and no visualization, confirming Hypothesis H1 that a detailed representation of hazards enhances perceived safety. This partially aligns with results Colley et al. [4], who observed significant increase in perceived safety (PSQ) when comparing (any) warning system with *no visualization* when investigating the effects of trajectory visualization in a car context.

7.2 AR Visualizations Reduce Subjective Workload

Our results show that the *Hazardous Area* concept yielded a significantly lower TLX score than the baseline, while the difference compared to *Hazardous Objects* was not significant. This supports H2 hypothesis which stated that *Hazardous Areas* would not increase subjective workload.

The significant reduction in subjective workload compared to no visualization represents an unexpectedly positive effect. Pupil diameter results showed no significant differences, so they do not contradict this finding.

Previous studies by Colley et al. [4] and Wang et al. [26] did not report significant differences in workload for their visualizations. However, they did not conduct equivalence testing, so their findings do not conflict with the present results.

7.3 Usability and User Experience

Hypothesis H3 proposes that *Hazardous Areas* exhibit comparable usability to *Hazardous Objects*. The user study results show that SUS scores for *Hazardous Areas* and *Hazardous Objects* are practically equivalent. An equivalence test (TOST) confirms this, and we therefore accept H3. *Hazardous Areas* achieve the benchmark rating of "excellent" [2], matching the established standard of *Hazardous Object* visualization.

The user study results show that UEQ-S scores for *Hazardous Areas* and *Hazardous Objects* are not significantly equivalent. No significant differences were detected either, so the hypothesis H4 (comparable UX between *Hazardous Areas* and *Hazardous Objects*) can neither be confirmed nor rejected. In absolute terms, *Hazardous Areas* perform very positively: they achieve the highest rank for pragmatic quality ("excellent") and the second-highest rank for hedonic and overall quality ("good"). *Hazardous Objects* only reach the third rank ("above average") in all categories, suggesting a trend in favor of *Hazardous Areas*. The ranking of conditions, where *Hazardous Areas* were rated significantly highest overall, further supports this trend. Since this ranking reflects overall user preference, it aligns with the observed user experience outcomes.

7.4 Overall Assessment

RQ1 asked how visualizing Hazardous Areas affects cyclists compared to Hazardous Object visualizations and a non-augmented ride. By structuring the investigation with sub-questions, we can interpret both objective and subjective effects.

Objective Riding Behavior (Research Question RQ1a). As many results were insignificant, this suggests a limited effect of the warning systems on objective cyclist and riding behavior. However, this interpretation is limited by study constraints—particularly the pronounced learning effect and limitations due to running a simulator study. Consequently, research question RQ1a cannot be fully answered. Further studies with larger participant samples are needed, allowing for stronger randomization and fewer hazardous events to reduce learning effects.

The few observable effects can be interpreted as follows:

- *Negative interpretation:* The increased head rotation with *Hazardous Objects* may indicate better situational awareness. Conversely, the reduced head movement with *Hazardous Areas* might reflect over-reliance on the system, which could be dangerous in real-world scenarios with potential false negatives. Some participants noted this concern during interviews.
- *Positive interpretation:* Reduced head deviation with *Hazardous Areas* could indicate better focus on the riding direction and immediate traffic, potentially lowering accident risk. *Hazardous Objects* may force riders to look around more, which could be distracting, as some participants reported.

The pupil diameter differences support the positive interpretation, suggesting that *Hazardous Objects* may reduce attention, aligning with the idea that *Hazardous Area* displays allow riders to concentrate more effectively on forward traffic. Additional studies are needed to clarify which interpretation predominates.

Subjective Riding Behavior (Research Question RQ1b). The system is highly accepted in terms of usability and user experience. Usability is comparable to that of *Hazardous Object* visualization, while user experience even shows a trend favoring *Hazardous Areas*.

The visualization of *Hazardous Areas* increases subjective safety and reduces perceived workload compared to *No visualization*. Even subjective safety is significantly higher than for *Hazardous Objects*. Higher perceived safety could lead to more relaxed and attentive riding, potentially improving objective safety. Conversely, excessive perceived safety might also encourage riskier behavior, as users may feel safer than they actually are.

Conclusion. Compared to no visualization, highlighting *Hazardous Areas* significantly increased cyclists' perceived safety while reducing perceived workload, which is especially valuable in complex traffic situations where cognitive resources are limited. Compared to highlighting individual *Hazardous Objects*, the visualization of *Hazardous Areas* produced higher perceived safety with comparable usability and equal or better user experience.

Head rotation analysis suggests a potential mechanism: cyclists deviated less from their forward direction when *Hazardous Areas* were shown than with *Hazardous Objects*. This indicates more efficient information processing, as cyclists can monitor potential hazard zones without constantly shifting attention to individual objects. Pupil diameter analysis showed no significant reduction with *Hazardous Areas*, whereas *Hazardous Objects* may reduce attention.

Concerns that increased perceived safety might encourage riskier behavior were not supported by the objective data, though study limitations prevent strong conclusions about behavioral changes. Future research in real-world scenarios should investigate this further.

7.5 Recommendations for Future AR Cycling Warning Systems

Based on our study findings and participant feedback, we extracted a set of recommendations that aim to support the development of future AR warning systems for cyclists.

A central tension concerns warning visibility. Some participants requested earlier and more extensive warnings, or even marking all vehicles, to allow more reaction time. Others reported being overwhelmed by too many warnings and preferred only immediate hazards to be shown. These conflicting preferences likely reflect different usage contexts. Overall, the current design appears to strike a reasonable balance, but future work could should carefully choose appropriate parameters for visibility and subtlety, for example through adjustable parameters or context-sensitive displays that reduce warnings in complex scenarios.

The need for **directional cues** was debated. Some participants stressed their importance and noted poor visibility, while others saw little value, as the hazard's direction was already obvious. Given the frequency of these comments, this aspect requires additional investigations. Future versions could highlight directional information only for unexpected hazards, providing guidance without overloading users.

Larger arrows, **color gradients**, or an animated "blurred future" showing predicted vehicle movement could enhance clarity, supporting the observed increase in perceived safety when hazard direction was clear (H1).

Our results suggest that warning systems should provide **longer lead times** to allow cyclists more reaction time. This recommendation aligns with participants' suggestions and the observed benefits of Hazardous Areas in reducing subjective workload (H2), indicating that earlier warnings may further improve riders' ability to react safely.

To reduce **information overload**, developers should carefully decide which hazards to show, in particular when multiple vehicles or other risks are present. Participants highlighted this issue, and the approach would reinforce the high usability and user experience observed for Hazardous Areas (RQ1b, H3). Potentially, future systems should allow for customization based on user preferences as user opinions differed regarding the desired amount of warnings.

For Hazardous Object visualizations, designers should increase **contrast** and add additional indicators for objects outside the peripheral view, as outlines were sometimes difficult to detect due to shadows or low contrast. Red or similarly colored vehicles were particularly challenging to see, suggesting that patterned outlines or larger **auras** could improve detection. These adjustments could complement the moderate subjective safety and workload improvements observed for Hazardous Objects.

Subtler presentations for Hazardous Objects can reduce **distraction** while maintaining awareness, and directional cues for approaching hazards, such as overtaking vehicles, should be clarified with arrows or other visual indicators. This reflects participant feedback about distraction and unclear cues, while aligning with our findings that Hazardous Areas enabled more focused attention.

Developers should be aware of **learning effects**, as participants quickly became familiar with routes and recurring hazard situations, limiting the observable effects on objective riding behavior (RQ1a). Systems should be designed to maintain attention over repeated exposure, preventing over-reliance on the AR visualization.

Care should be taken to balance **perceived safety** and **cognitive load**, since some participants reported reduced attention when relying on the warning systems. This aligns with our discussion of potential overconfidence effects and the need to avoid false negatives in real-world scenarios.

8 Conclusion and Future Work

This work investigated the visualization of *Hazardous Areas* as a novel concept for bicycle warning systems. A user-centered design was developed based on focus group insights and evaluated in a within-subjects user study using a VR bicycle simulator, which was technically enhanced as part of this research.

Results indicate that the visualization of *Hazardous Areas* is a promising alternative to conventional object-based warnings. It increased perceived safety, reduced subjective workload compared to no visualization, and achieved high ratings in usability and user experience, suggesting strong user acceptance. While no significant effects on objective driving behavior were found, this is likely due to study limitations.

Future research should examine the combination of the visualization of *Hazardous Areas* with auditory or haptic modalities, as well as methods for detecting and spatially estimating hazards in real traffic, potentially through machine learning. Larger user studies are needed to validate objective effects and mitigate learning biases. Further design optimization should address the balance between visibility and subtlety, improve directional cues, and explore hybrid approaches combining area- and object-based warnings.

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A Appendix

A.1 List of Used Assets

All of the following assets and licenses were last accessed on July 16, 2025, and used in this form.

A.1.1 Licenses. The following table provides an overview of the licenses under which the assets used had been published:

Name	Source
Standard Unity Asset Store EULA	https://unity.com/legal/as-terms
Mixkit Sound Effects Free	https://mixkit.co/license/#sfxFree
CC BY 4.0	https://creativecommons.org/licenses/by/4.0/

A.1.2 Assets subject to a fee. The following paid assets were used:

Name	Author	License	Source
City Constructor	LowlyPoly	Standard Unity Asset Store EULA	https://assetstore.unity.com/packages/3d/environments/urban/city-constructor-227767
Urban Low Poly People	AGLOBEX	Standard Unity Asset Store EULA	https://assetstore.unity.com/packages/3d/characters/humanoids/urban-low-poly-people-62916

A.1.3 Free Assets. The following free assets were used:

Name	Author	License	Source
80s Generic midsize sedan – Low poly model	Daniel Zhabotinsky	CC BY 4.0	https://sketchfab.com/3d-models/80s-generic-midsize-sedan-low-poly-model-e2678da920cc4be68dbc193727919ffb
'80s Generic USA Station wagon – Low poly model	Daniel Zhabotinsky	CC BY 4.0	https://sketchfab.com/3d-models/80s-generic-usa-station-wagon-low-poly-model-aa0becb6e854422596cac6b21bf79787
American Muscle '71 – Low poly model	Daniel Zhabotinsky	CC BY 4.0	https://sketchfab.com/3d-models/american-muscle-71-low-poly-model-955edc733c6d44fabc0ad7c246a15896
City Compact '95 – Low poly model	Daniel Zhabotinsky	CC BY 4.0	https://sketchfab.com/3d-models/city-compact-95-low-poly-model-122a22d210234596ad23623588d0d166
Compact Pickup '78 – Low poly model	Daniel Zhabotinsky	CC BY 4.0	https://sketchfab.com/3d-models/compact-pickup-78-low-poly-model-30700a84311c4bea9ef722f0773ce92a
Italian Group A '89 Hot Hatch – Low poly model	Daniel Zhabotinsky	CC BY 4.0	https://sketchfab.com/3d-models/italian-group-a-89-hot-hatch-low-poly-model-97b15b067111443ebe05840137b49c65

Name	Author	License	Source
Japanese sedan ’86 – Low poly model	Daniel Zhabotinsky	CC BY 4.0	https://sketchfab.com/3d-models/japanese-sedan-86-low-poly-model-5c17c582ef9549798f694b660feea42a
Old Panel van – Low poly model	Daniel Zhabotinsky	CC BY 4.0	https://sketchfab.com/3d-models/old-panel-van-low-poly-model-09d718c9cf72401b8534d265a06a803f
Classic car horn	Mixkit	Mixkit Sound Effects Free	https://mixkit.co/free-sound-effects/car/
Town Houses Pack	ChermandirKun	Standard Unity Asset Store EULA	https://assetstore.unity.com/packages/3d/environments/urban/town-houses-pack-42717
Modular Period Building No 1, Munich, 1900	Sybaris	Standard Unity Asset Store EULA	https://assetstore.unity.com/packages/3d/environments/historic/modular-period-building-no-1-munich-1900-190294
Russian buildings pack	MadMedicSoft	Standard Unity Asset Store EULA	https://assetstore.unity.com/packages/3d/environments/urban/russian-buildings-pack-113375
Road System	Maxi Barmetler	Standard Unity Asset Store EULA	https://assetstore.unity.com/packages/tools/level-design/road-system-192818
Mountain bike	Niilo Poutanen	CC BY 4.0	https://sketchfab.com/3d-models/mountain-bike-1d9270f82a34460e928709bbf7709d56
European Road Signs	Satik64	CC BY 4.0	https://sketchfab.com/3d-models/european-road-signs-25ebbe36a9274344bd779a55d97bfca3
Modular Russian Road Signs Pack (URBAN)	Unka II	CC BY 4.0	https://sketchfab.com/3d-models/modular-russian-road-signs-pack-urban-5d6e2672d73c44b3b0f7bf62e43fad55
Modular Street Signs (Asset Pack)	SAGEKING	CC BY 4.0	https://sketchfab.com/3d-models/modular-street-signs-asset-pack-850935dd380a4e4db0c4846d2fe6e783

A.2 Disclaimer

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