BikeAR: Understanding Cyclists' Crossing Decision-Making at Uncontrolled Intersections using Augmented Reality

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Figure 1: Overview of two visualization concepts to support cyclists' crossing decision-making at visually occluded urban environments: X-ray highlights occluded cars (left) and Countdown displays time the intersection remains safe to cross (right).

ABSTRACT

Cycling has become increasingly popular as a means of transportation. However, cyclists remain a highly vulnerable group of road users. According to accident reports, one of the most dangerous situations for cyclists are uncontrolled intersections, where cars approach from both directions. To address this issue and assist cyclists in crossing decision-making at uncontrolled intersections, we designed two visualizations that: (1) highlight occluded cars through an X-ray vision and (2) depict the remaining time the intersection is safe to cross via a Countdown. To investigate the efficiency of these visualizations, we proposed an Augmented Reality simulation as a novel evaluation method, in which the above visualizations are represented as AR, and conducted a controlled experiment with 24 participants indoors. We found that the X-ray ensures a fast selection of shorter gaps between cars, while the Countdown facilitates a feeling of safety and provides a better intersection overview.

CCS CONCEPTS

• **Human-centered computing → Interactive systems and tools**; **Mixed / augmented reality**.

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KEYWORDS

augmented reality, cyclist safety, crossing decision-making

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1 INTRODUCTION

With the growing public awareness of climate change and the associated ecological transformation of individual mobility, the proportion of cyclists in road traffic is rising constantly [43], reaching 26% of the population in the Netherlands, 18% in Denmark, and 10% in Germany [42]. However, the increase in the number of cyclists does not imply an increase in their safety. While car drivers are protected with different active and passive safety systems, such as crumple zones, airbags, emergency brake and intersection crossing assistants [4–6], cyclists remain among the most vulnerable road users [1, 50]. According to accident reports [9, 17, 25], one of the most dangerous situations for cyclists remain uncontrolled intersections with cars approaching from both directions. With a constant traffic flow in occluded urban environments, e.g., in congested cities or through a future flow of autonomous vehicles, the crossing decision-making at uncontrolled intersections becomes even more difficult for cyclists and requires a better understanding of their crossing strategies.

In their attempts to assist cyclists, researchers utilized a broad range of approaches, from multimodal assistance systems to projected surfaces and head-up displays. The former ones typically combine ambient light [32], vibrotactile [52], and auditory [30] feedback in helmets and on bicycles, and latter ones [11, 31, 33] augment surrounding environment with relevant information around cyclists on the road and in front of them. Although these approaches have shown promising results, the technical components and visualizations have a couple of shortcomings. Firstly, they are typically coupled to cyclists' egocentric perspective and do not consider the objects decoupled from cyclists' egocentric perspective, e.g., occluded vehicles at uncontrolled intersections. Secondly, they are usually placed on the particular parts of the bicycle and body, eliminating the spatial link between warnings and the real world. Therefore, given that existing assistance systems often fail to convey the above-mentioned aspects, this paper aims to explore the objects decoupled from cyclists' egocentric perspective, which require special consideration for increasing situational awareness.

To overcome the aforementioned shortcomings of existing presentation approaches, in this paper, we investigate cyclists' crossing decision-making through the prism of Augmented Reality (AR) and leverage the unique capabilities of AR over traditional (fixed-position) display technologies. For this, we designed two types of visualizations: (1) X-ray – highlights occluded cars through an X-ray vision and (2) Countdown – depicts the remaining time the intersection is safe to cross (Figure 1). To evaluate these visualizations, we utilized an Augmented Reality simulation as a novel approach to create an immersive and realistic study setup. This allows participants to cycle in a safe physical environment, such as an indoor space or a confined parking lot, on a real bicycle through a purely virtual world rendered by the AR glasses. Furthermore, the virtual representation of the world allows mimicking dangerous situations without exposing participants to any danger. We used Augmented Reality glasses to create a virtual environment where the above visualizations are displayed as AR rather than VR for safety reasons, such as avoiding biking into walls. In the controlled indoor experiment (N=24) based on the proposed AR approach, we investigated how well cyclists can make a crossing decision at uncontrolled intersections using visualization techniques. We showed that the X-ray visualization ensured a fast selection of shorter gaps between cars. In contrast, the Countdown visualization facilitated a feeling of safety and provided a better intersection overview. Additionally, our results indicated that our proposed AR-based approach is suitable for conducting user studies with cyclists.

In summary, our research contribution includes:

(1) An empirical evaluation of cyclists' crossing decision-making at uncontrolled intersections using the AR-based visual assistance decoupled from cyclists' egocentric perspective using our proposed AR-based simulation environment.
(2) An AR-based approach for conducting user studies with cyclists in real-world physical environments using a 3D simulation.

2 RELATED WORK

Although there has not been much work on bicycle safety systems focused on assistance with augmented reality, researchers have designed several support systems for cyclists in general. In this section, we examine existing work in this area, followed by a discussion of supporting cyclists in crossing decisions.

2.1 Cyclist Assistance Systems

Since the bicycle's invention over 200 years ago, technological advances in cycling have come a long way in making cycling safer. It began with changes to the physical factors of the bicycle, such as equal-sized wheels and a low center of gravity, to make the bike more stable and safer [21], and reached the stage of enhancing bicycles and their accessories with electric motors, additional assisting signals, and cues. While engineers have reached a consensus for designing safer bicycles from an ergonomics perspective, the design of additional aid signals still has a long way to go. To date, these aids have been based primarily on multimodal approaches that combine ambient light, vibrotactile, and auditory feedback on the bicycle and helmet with projected surfaces and head-up displays that augment the cyclist's environment. We provide a detailed overview of these two approaches below.

2.1.1 Multimodal assistance systems. Multimodal approach for assisting cyclists has utilized ambient light, vibrotactile, and auditory feedback to represent navigation cues [11, 32], warning signals [30], and safety recommendations [31, 33], located on the bicycle and helmets. While many commercial products for cycling navigation employed on-bicycle visual systems, such as Hammerhead [1], researchers investigated visual, auditory and tactile displays integrated into the helmets and handlebars. TactiCycle was one of the pioneering works, which utilized vibration motors in the handlebar for turn-by-turn navigation [39, 41], which was later on commercialized by SmartGrips [2]. Recently, Matviienko et al. [32] investigated navigation cues via vibration, auditory cues, and ambient light integrated into helmets for child cyclists and found that auditory navigation was the most preferred.

Like navigation cues, most systems with warning signals also primarily rely on the multimodal approach. For example, Garmin Varia Rearview radar [3] is a bike accessory that provides warnings regarding the vehicles approaching from behind with a visual notification on the screen fixed to the handlebar. Schopp et al. [49] augmented a helmet with a bone conductive speaker to warn cyclists about approaching, out-of-view vehicles. The results of their experiment showed increased situational awareness and indicated that cyclists could better identify dangerous situations. Jones et al. [23] took a step further and augmented a helmet with both input and output methods. They tracked head tilts as an indication of cyclist intentions and showed turn signals on the back of a helmet. Moreover, the combination of visual, vibrotactile, and auditory signals is efficient in implying an immediate action of braking [30].

2.1.2 Projected surfaces and head-up displays. Alternatively, researchers and engineers investigated projected interfaces and head-up displays in commercial products and research projects to the multimodal approach. Projected interfaces have been explored for

[1] https://www.theregister.com/2015/07/12/review_hammerhead_satnav_for_cyclists/, last accessed 22nd February 2022
[2] http://smrtgrips.com/, last accessed 22nd February 2022
[3] https://road.cc/content/review/246451-garmin-varia-rtl510, last accessed 22nd February 2022

obstacle detection on the road, such as visualization of potholes [4], or cyclists' visibility via a projected bicycle sign in the front [5]. However, it has been previously shown that projected surfaces were harder to see in bright environments and drivers felt safer with head-up displays [11, 31]. As for the head-up displays, the glasses by Everysight [6] displays necessary information in front of a cyclist's eyes using OLED technology and a newly introduced helmet SKULLY AR-1 [7] employs a similar idea to show information about speed, navigation, and nearby vehicles in the corner of a helmet's visor. Both products display instructions without blocking the view in a subtle and non-distracting way. Head-up displays have also been shown helpful in experiments with child cyclists for trajectory adjustment [31] and reminding about safety gestures [33].

In summary, researchers have previously designed several support systems for cyclists based on multimodal approach, projected surfaces, and head-up displays. Despite the success of the multimodal approach to support cyclists, it usually requires multiple devices placed in different locations, which can become cumbersome and non-practical. Projected surfaces have visibility limitations, and head-up displays show information from the egocentric perspective to the user independently from head movements. The egocentric information representation lacks the environmental information necessary to increase awareness of the surrounding environment. To overcome this issue, in this work, we explore an Augmented Reality (AR) approach as an alternative to the presented solutions. AR enables the merging of information with the real world, e.g., displaying occluded cars based on car-to-X technology.

In addition to the advantages of AR as a solution to support cyclists, we propose this technology as a tool to facilitate a safe 3D simulation environment for user studies without introducing danger for cyclists. To date, most of the evaluations have been conducted in the stationary indoor simulators with the simulation projected on the wall or displayed in the VR headset, and the restricted outdoor areas without additional traffic for safety reasons, except for several works which explored contextual technology [51, 59] and bicycle cooperation [2, 3] in outdoors studies. AR allows us to increase the ecological validity of the existing results and explore the cycling behavior while cycling on a real bicycle and see virtual 3D cars augmented in the real world.

2.2 Decision-making in Traffic Flow

Timely decision-making in traffic flow plays a vital role in road safety. For vulnerable road users, such as cyclists, it is a very crucial issue since collisions with motorized vehicles might lead to severe injuries or even fatalities. According to the latest statistical reports on traffic accidents, one of the most dangerous locations for cyclists are intersections, where cars are coming from left, right, or both directions [9, 17, 25]. To assist cyclists at intersections, we look at possible ways to increase their awareness of the traffic situation and provide the necessary information to make a safe crossing decision. To achieve this, we build on the existing body of work for supporting pedestrians and cyclists' decision-making, which we outline in the following.

2.2.1 *Supporting pedestrian decision-making.*

Previously, researchers have primarily investigated the issue of road crossing for pedestrians [12, 13]. It implies that the decision has to be made statically by standing at the intersection [29] or crossing while engaged in a secondary task, e.g., texting [44, 45]. Passive and active approaches have been utilized to support pedestrians' crossing decision-making. The *passive approach* focused on the communication between pedestrians and autonomous vehicles via information augmentation of the surrounding environment, on-vehicle displays, or smartphones. For example, Loecken et al. [27] explored interaction concepts placed in the environment and on autonomous vehicles, such as eye contact, a smile, and familiar concept from the real world, such as zebra projections. Their results showed that participants preferred a familiar crossing concept based on the zebra-crossing visualization. Mahadevan et al. [28] explored a multimodal passive interaction between autonomous vehicles and pedestrians and found that interfaces with explicit communication of the vehicle's intent help pedestrians to make crossing decisions. Rahimian et al. [44, 45] employed hand-held devices to warn pedestrians about upcoming traffic while crossing a road and have shown the importance of warning signals for guiding pedestrians attention. Similar results have been shown by Malik et al. [29], who have compared prohibitive and permissive alerts on a smartphone for younger and older adults, and found that they were highly likely to heed permissive alerts. The *active approach* employed the usage of gestures to convey the intends of pedestrians. For example, Gruenefeld et al. [19] added gesture-based interaction between pedestrians and automated vehicles in addition to on-car displays. However, their VR-based evaluation showed that participants struggled with performing the gesture correctly, and the interaction led to increased hesitation to cross the road. Due to the previous success of the passive approach, in our work, we aim to augment the surrounding environment based on the familiar real-world metaphors and enable crossing decision-making without active interaction with a traffic flow.

2.2.2 *Supporting cyclist decision-making.*

Making decisions while cycling is more challenging due to the higher speed of cyclists and dynamic decision-making compared to pedestrians. Although Andres et al. proposed systems that promote cooperation between the user and the bicycle, both cognitively [3] and physically [2], they primarily focus on speed control for catching "green waves" and estimation of cyclists' peripheral awareness through neural activity. By "green waves" we refer to changes in a series of traffic lights that facilitate continuous traffic flow over several intersections in one main direction. Several other works have specifically investigated the perception of vehicle gaps and crossing decisions for child and adult cyclists. For example, Plumert et al. [40] examined the influence of sparse and dense traffic flows in a stationary bicycle simulator and found that high-density intersections led participants to take narrower gaps. Grechkin et al. [18], on the other hand, examined the influence of bidirectional traffic flow and found that both children and adults preferred rolling to aligned pairs of gaps to cross. Chihak et al. [7] examined differences in speed adaptation between children and adults approaching intersections and found

[4] https://newatlas.com/lumigrids-led-projector/27691/, last accessed 22nd February 2022
[5] https://beryl.cc/shop/laserlight-core, last accessed 22nd February 2022
[6] https://everysight.com/, last accessed 22nd February 2022
[7] https://wearabletech.io/skully-fenix-ar-helmet/, last accessed 22nd February 2022

that children tend to overcorrect in speed and cross less safely than adults. However, the previous three experiments were conducted in the stationary bicycle simulators and focused on cyclists' perception and cycling behavior rather than technological assistance. To technologically assist cyclists at intersections, von Sawitzky et al. [54] have introduced three concepts with head-up displays to improve road safety for cyclists, which include seeing through walls, a smart path for crossing, and warning signs. Their results were based on the subjective data and indicated that seeing through walls and smart bicycle paths were rated as the most preferred information quality and quantity methods. In our work, we take a step further and evaluate assistance concepts for cyclists in the experiment on an actual bicycle to increase the ecological validity of the results by mimicking a realistic cycling experience.

As can be seen from the previous work, traditional interactions between motorized vehicles and pedestrians play a fundamental role in influencing the pedestrian's crossing decision, which relies on the vehicle's speed and distance to estimate both the awareness and the intent of the driver [48, 53, 55]. Although pedestrians and cyclists receive additional information about what a car intends to do with an introduction of on-vehicle displays, they still heavily rely on the drivers' behavior inside the vehicles. On the other hand, the augmentations of the environment based on the familiar metaphors, such as zebra-crossing, are often perceived as more efficient and trustworthy. In this paper, we build on these two ideas of decision-making based on the traditional speed and distance estimation and familiar metaphors. For this, we designed two visualizations to assist cyclists in making crossing decisions. We also aimed to provide on-the-go dynamic assistance so that cyclists do not have to stop every time they make a crossing decision. We describe our proposed AR-based approach for conducting user studies with cyclists and both types of visual assistance in the following sections.

3 AR-BASED APPROACH FOR CONDUCTING USER STUDIES WITH CYCLISTS

Controlled experiments with cyclists often face a trade-off between close-to-reality environments and participants' safety. On the one hand, researchers aim to create experimental conditions that resemble the real world as closely as possible while, on the other hand, ensuring the physical safety of the participants. To create safe cycling conditions, researchers have previously designed fixed indoor bicycle simulators with on-the-wall projections [30, 32], screen walls [31], or virtual reality headsets [26, 36, 54]. However, one of the main limitations of such setups is the lack of a full cycling experience, including balance, coordination, and physical movement through space. As a first step to increase the ecological validity, researchers conducted experiments on restricted outdoor areas [11, 33, 58], test tracks [10, 31], which are typically used for car driver training, and under real traffic conditions [59]. However, mimicking hazardous situations under such conditions without endangering participants remains a challenging task. Moreover, technical aspects of the experiment, such as data logging, power supply, and lighting conditions, are very time-consuming and require thorough planning and effort.

With our proposed AR-based approach for conducting user studies with cyclists, we aim to bring evaluations one step closer to safe yet close-to-reality environments. This approach combines movement in the physical world while going through the virtual environment shown in the augmented reality glasses. It facilitates an increase of ecological validity of user studies and enables simulation of hazardous situations without harm for participants. Given that the virtual environment is shown in augmented reality glasses, participants still see the physical world for safety reasons, compared to, for example, virtual reality headsets that block the field of view entirely.

From the technical side, modern augmented reality glasses, such as Microsoft Hololens 2 [8], allow a wide field-of-view, have a long-lasting battery and enable live logging of the data directly on the device, similarly to indoor bicycle simulator. The live logging removes the necessity of additional hardware for data logging, which is usually required for outdoor experiments. Visibility of information in the glasses remains restricted to outdoor lighting conditions, but it is ideally suited for indoor experiments with adjustable lighting conditions.

The virtual part of our approach is built using modular blocks, which can be reconnected in real-time. Each city block allows a cyclist to turn left, right, or continue going straight at every intersection. For this, we defined five types of city blocks, i.e., virtual voxels, which include: (1) turning left, (2) turning right, (3) going straight, (4) X-crossing, and (5) T-crossing. By reconnecting previous and adding new city blocks outside the user's field of view, this setup allows replication of a locomotion effect and the creation of comparable trajectories for the experiment. It facilitates the enlargement of the virtual cycling area in the limited physical space without interfering with users' cycling experience. With this, we are confident that we can successfully increase the ecological validity of experiments with cyclists in controlled and safe environments.

4 AUGMENTED REALITY ASSISTANCE FOR CYCLISTS AT INTERSECTIONS

To evaluate the feasibility of the aforementioned AR-based approach and to better understand the decision-making strategies of cyclists at intersections, within the scope of this paper, we explored two types of augmented reality assistance: (1) X-ray and (2) Countdown (Figure 1 and 2).

4.1 X-ray

This visualization aims to mimic driving in open non-occluded rural areas while cycling in urban areas. Driving in non-occluded rural environments allows seeing crossing traffic from a long distance, compared to the occluded environments that cover a big part of the field of view in urban areas. Therefore, the X-ray visualization shows the crossing traffic as a virtual augmentation on occlusions allowing us to see relevant information through occlusions, similar to X-ray vision. With this, we aim to facilitate safe on-the-go crossing decision-making before reaching the crossing.

4.2 Countdown

To safely cross a street, people usually rely on a distance to a vehicle and its speed [8, 48, 53, 55]. These factors play an essential role

[8] https://www.microsoft.com/en-us/hololens

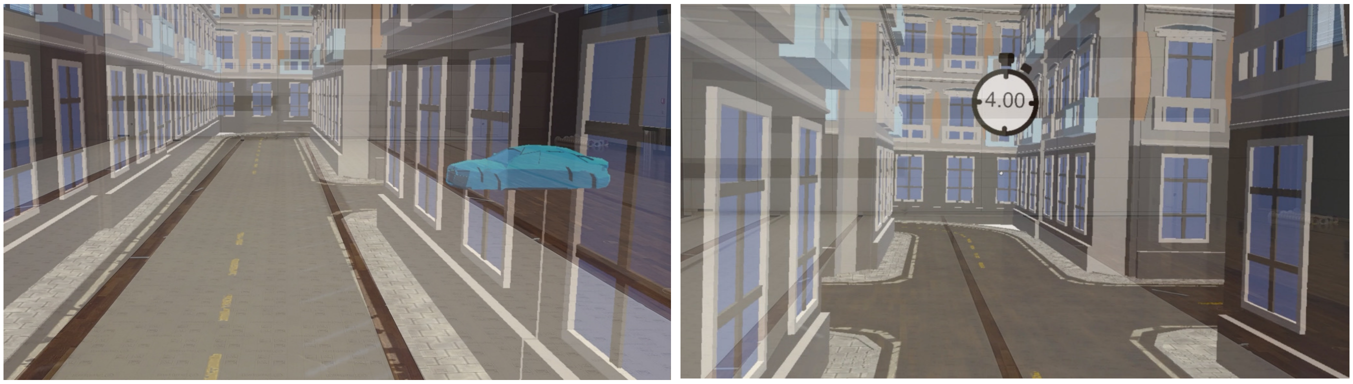

Figure 2: Two types of visualizations to support cyclists' decision-making at intersections: (1) X-ray – highlights occluded cars through an X-ray vision (left) and (2) Countdown – depicts the remaining time the intersection is safe to cross (right). The figure depicts a first-person perspective on the AR simulation of the city from the inside of the AR headset with a physical indoor hall in the background, as it was shown to participants during the experiment.

in a time estimation to make a road crossing decision. Therefore, this Countdown visualization depicts only one timer above each intersection, showing the remaining time for the next car to arrive. The car's arrival means that the Countdown indicates the time remaining until the car enters the intersection, i.e., how much time is left until the front of the car enters the intersection. In the case of bidirectional traffic, the Countdown displays a minimum of remaining times for both traffic flows.

4.3 Design Considerations

We based the X-ray on previous ideas in VR/AR and urban research [54], and the Countdown on a traffic light metaphor with a timer [15]. With this work, we provide a novel contribution by exploring both ideas in the dynamic nature of cycling as a particular use case. Although within the scope of this paper, we focus on the visualization of occluded cars, the concept of the X-ray can be further extended to show other road users, e.g., cyclists, e-Scooter riders, and pedestrians. We placed the Countdown in the environment instead of the handlebar to glancing down, causing additional distractions and a lack of spatial connection to the respective intersection. Therefore, the AR Countdown in the user's direct Field-of-View can retain focus on the traffic.

We chose these two particular visualizations because they are complementary in dimensions of spatial overview and precision. While the Countdown is precise in information presentation, it might lead to a worse intersection overview. On the other hand, the X-ray might provide a better intersection overview with less precision. We explicitly designed the Countdown as a stopwatch to ensure the precision of information compared to more abstract visualizations, e.g., bars and segments, or spatial visualizations, such as the X-ray. Given that gaps are typically measured by time, we decided to show them explicitly as an actual time compared to the X-ray, where time gaps have to be estimated by cyclists. This also means that the Countdown is more sensitive to changes in vehicle speed than the X-ray. In situations where vehicles accelerate or decelerate, the changes are immediately visible. However, the changes displayed in the Countdown can be perceived more quickly than in the X-ray because the information is concentrated in one place (the Countdown), unlike the spatially distributed visualizations (the X-ray). Moreover, both concepts are based on the support of cyclists in visually occluded urban environments and dynamic communication between cyclists and cars via broadcast messages with position and velocity information. We envision both AR visualizations to rely on a Car2X technology [38], which enables an exchange of messages between traffic members, broadcasting their speed and location, to avoid collisions. Based on the received information, the AR assistance system can visualize the occluded cars and the remaining time for the cars to reach an intersection.

5 EVALUATION

To investigate cyclist crossing decision-making at uncontrolled intersections using the two proposed AR-based visualizations (Figure 2), we conducted an indoor experiment in the augmented reality simulation on a bicycle based on the proposed AR approach.

5.1 Participants

We recruited 24 participants (12 female, 12 male) between 16 and 56 years (M = 28.3, SD = 7.9) using social networks and personal contacts. All of the participants had no hearing problems and had normal or corrected vision without color blindness. Additionally, we have received written permission from the parents of the 16-year old participant.

5.2 Apparatus

To create a more realistic cycling experience in comparison to the previous evaluations in bicycle simulators [30, 32, 52] and to ensure consistent lighting conditions, participants cycled on a bicycle (28-inch, 1.8 meters long) in an empty indoor hall (33 x 17 meters) while wearing augmented reality glasses (Figure 3). The virtual environment was implemented using Unity game engine and shown in Microsoft HoloLens 2 Augmented reality headset with a diagonal field of view of 52°.

To create a virtual city, we used a set of four tiles: (1) corner, (2) straight street, (3) T-intersection, and (4) intersection (Figure 4). All

Figure 3: Participants cycled in the indoor hall on an actual bicycle while seeing the virtual world through augmented reality glasses and the real world via peripheral vision for safety measures.

tiles have a size of 4.5 by 4.5 meters, leaving 3.5 meters for the street and 0.5 meters for the building facades. Connecting the tiles and taking into account the dimensions of the hall, it is possible to create the virtual city based on a grid of 3 by 7 tiles (13.5 meters by 31.5 meters). To facilitate a single continuous ride for each experimental condition, we used invisible checkpoints to detect the position of a cyclist and rearranged the tiles to create a new road. This change was not visible to cyclists since it was happening behind them. In this way, we altered the city a total of twenty times per each experimental condition (Figure 3). The segments between intersections were 30 to 35 m (or six to seven segments) long.

From the hardware side, the glasses were used off-the-shelf without additional tracking support. To specify the origin of the virtual city, the glasses had to be placed at the designated location on the floor before each experimental condition.

5.3 Study design

The study was designed to be within-subject with two independent variables: (1) type of assistance and (2) traffic density. For the type of assistance, we used X-ray, Countdown, and no assistance as a baseline (Figure 2). For the traffic density, we explored dense and sparse traffic flows.

To create different levels of traffic density, we varied traffic direction and car gaps. For the traffic direction, we explored three situations, where cars are coming from (1) left, (2) right, and (3) both directions, based on statistical reports [9, 17, 25]. The cars drove in a continuous stream. With this, we aimed to create conditions under which participants were forced to make crossing decisions using visual assistance and avoid situations where they could wait until the cars passed by.

For the car gaps, we calculated a stopping distance (7.5 m) based on the car speed (15 km/h for all cars) and asphalt friction coefficient for dry roads (k = 0.7). Given the differences in speed and distance perception between the virtual and real worlds [56], we set the speed of cars in Unity to a constant 15 km/h to reflect a realistic speed perception in VR [26]. The 50 km/h speed limit for urban environments is perceived as higher in a virtual environment, making it impossible to solve the intersection task without an accident. This does not mean that lower speeds are perceived realistically, and higher speeds of other vehicles seem unrealistic. However, the smaller size of the surrounding buildings and the length of cars (2.4 m) played a role in perceiving car speeds. The reason for this is that although the surrounding buildings and cars are smaller, the virtual size of the objects still reflects reality, so the speed of 50 km/h is not suitable. Moreover, the evaluation approach imposed a limited physical space and forced us to reduce traffic speed to take into account the limited visual range. To simulate a realistic road situation despite the space restrictions, we reduced the speed of traffic and the distances between the individual vehicles correspondingly. It allowed us to obtain a comparable time gap for crossing the road as in real traffic and generalize the result for other traffic speeds. Additionally, the limited physical space of the indoor hall forced us

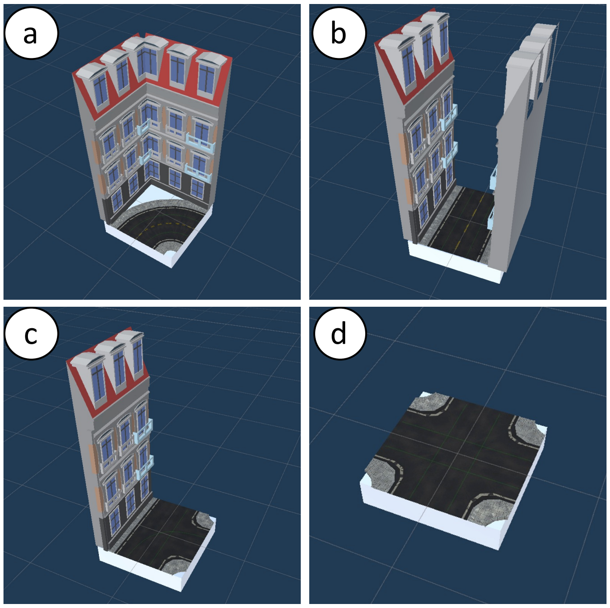

Figure 4: Tiles used to create the virtual city: (a) corner, (b) straight street, (c) T-intersection, and (d) intersection. They are the building blocks of the virtual city simulation, and their dynamic rearrangement facilitates continuous cycling.

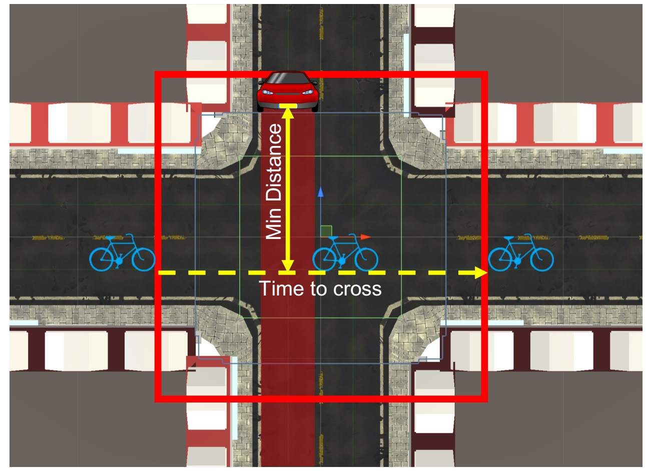

Figure 5: The measured time to cross is between entering a red boundary box with a front wheel and leaving it with a rear wheel, i.e., time spent cycling along a dashed yellow line. The minimum distance to cars (solid yellow line) was measured between a front bumper of an approaching car and a cycling trajectory when a bicycle was leaving a projected car's driving trajectory (dark red) with a rear wheel. In the case of bidirectional traffic, the minimum of both distances was taken as a minimum distance to cars.

to create a slightly disproportional urban landscape of the simulation, e.g., smaller turning radii at intersections and close proximity of buildings to each other. However, it was necessary to facilitate a continuous cycling experience within a limited physical space.

To thoroughly explore cyclists' decision making and see which gap they select, we prepared five types of car gaps with a quarter step in relation to the stopping distance: 7.5 m (1.8 sec), 9.5 m (2.3 sec), 11.5 m (2.7 sec), 13 m (3.2 sec), and 15 m (3.6 sec), which is mapped to 100% (a stopping distance), and 125%, 150%, 175%, 200% of the stopping distance. These car gaps were used for unidirectional traffic flow and formed a dense traffic flow. To create a sparse traffic flow, we doubled these distances: 15 m (3.6 sec), 19 m (4.5 sec), 22.5 m (5.4 sec), 26 m (6.3 sec), and 30 m (7.2 sec). The gaps were further doubled for the bidirectional traffic, given two traffic flows. For this, we used gaps of 15 m (3.6 sec), 19 m (4.5 sec), 22.5 m (5.4 sec), 26 m (6.3 sec), and 30 m (7.2 sec) for a bidirectional dense traffic flow and gaps of 30 m (7.2 sec), 38 m (9.0 sec), 45 m (10.8 sec), 52 m (12.6 sec), and 60 m (14.4 sec) for a bidirectional sparse traffic flow. The temporal relationship between gaps in the adjacent lanes was random to create diverse crossing opportune moments. This allowed us to create two traffic densities: (1) dense and (2) sparse.

5.3.1 Experimental conditions. To explore all levels of independent variables, we created six experimental conditions (3 types of assistance x 2 traffic densities) that include all possible combinations of car gaps and traffic directions. We took the most dangerous situation based on prior statistical reports, which show that junctions, where a car was approaching either from left, right, or both directions, lead to the highest number of car-to-cyclist accidents [9, 17, 25]. To facilitate a single continuous journey in a virtual city, the participants' task was to always follow the course of a road in a limited physical space and turn left at a T-junction. They were informed about different gaps and directions of car flows and were asked to cross each intersection without being hit by a car. Participants could wait as long as necessary before crossing the intersection. In total, within each condition, every participant experienced twenty intersections. At twelve of these intersections, a traffic flow was coming four times from the left, four times from the right, and four times from both directions, presented in the randomized order. The remaining eight intersections had no traffic flow and no visualizations. The sequence of six conditions was counterbalanced using a Latin square. At each intersection, participants experienced all four types of car gaps in a randomized order.

5.4 Procedure

For this study, we adhered to our universities health department's guidelines for user studies during the COVID-19 pandemic. All testing equipment was disinfected and the hall used was aired out for a minimum of one hour between participants. After obtaining informed consent, we collected participants' demographic data. Afterward, we provided a brief overview of the procedures, which included explanations of both visualizations. Participants familiarized themselves with a provided bicycle, the indoor environment, our augmented reality simulation, and visualizations during a test ride. Once the participants felt comfortable, we started experimental conditions with cycling in the simulation while wearing the augmented reality glasses. During the experiment, participants had to cycle on a bicycle in the empty hall through a virtual city

	Time to cross, s		Accident rate, %		Distance to cars, m		TLX score		Frequent Gap selection, s	
	Sparse	Dense	Sparse	Dense	Sparse	Dense	Sparse	Dense	Sparse (U/B)	Dense (U/B)
No vis.	4.2	6.2	20	37	7.9	6.9	34.1	44.5	5.4/9.0	3.6/5.4
Countdown	2.3	4.8	17	44	8.1	5.9	32	45.3	4.5/7.2	3.6/5.4
X-ray	3	4.4	18	37	7.5	6.2	29.5	33.7	5.4/7.2	3.6/4.5

Table 1: Summary of results: means for time to cross, accident rate, distance to cars, TLX score, and the most frequently selected gaps. U = unidirectional traffic, B = bidirectional traffic, TLX = Task load index.

shown in the augmented reality glasses. Their task was to make a safe crossing decision at every intersection. When they observed a visualization, they were free to choose how they would like to make crossing decisions: by stopping or making a crossing decision on-the-go. At the end of the study, we interviewed the participants about their preferences for the different visualizations and immersiveness of the bicycle simulation. The cycling part of the study took about half an hour and the entire study lasted approximately one hour. The study was conducted with approval from the ethical review board at our university.

5.5 Measures

To compare two types of assistance for cyclists, we measured the following dependent variables:

- *Time to cross (in seconds):* for each intersection with a traffic flow, we measured the time cyclists spent at and inside an intersection. For this, intersections were equipped with boundary boxes. As soon as participants entered this box, they could stop, thoroughly observe the intersection, and wait for a large enough gap to cross. The timer started when a bicycle's front wheel entered the boundary box of the intersection and stopped when the rear wheel left it (Figure 5).
- *Accident rate:* for each condition, we counted the number of occurrences a cyclist virtually crashed into a car.
- *Gap selection (in seconds):* for each intersection with a traffic flow, we logged a type of gap between cars cyclists chose for crossing. In the case of bidirectional traffic, the minimum of gaps from each traffic flow (= the shorter gap) was taken as a selected gap.
- *Minimum distance to cars (in meters):* for each intersection with a traffic flow, we measured the shortest distance between cars and cyclists when leaving an intersection after crossing. The minimum distance to cars was measured between a front bumper of an approaching car and a cycling trajectory when a bicycle was leaving a projected car's driving trajectory with a rear wheel. In the case of bidirectional traffic, the minimum of both distances (= the shorter distance) was taken as a minimum distance to cars (Figure 5).
- *Perceived workload:* for each condition, we asked participants to specify the perceived workload using the NASA Task Load Index, which covers the workload in terms of mental demand, physical demand, temporal demand, overall performance, effort, and frustration level [20].
- *Safety, visual assistance, and intersection overview:* for each condition, we asked participants to specify how safe they felt, how appropriate the assistance was, and how good the overview of the intersection was using a 5-point Likert scale.

6 RESULTS

We found that we can assist cyclists at uncontrolled intersections using AR-based visual assistance and accelerate decision-making. The summary of results from our evaluation is shown in Table 1. We used Repeated-Measures ANOVA and t-tests for post-hoc analysis of the parametric data. For non-parametric data, we applied the aligned rank transform for non-parametric factorial analyses [57]. We outline all results in detail in the following.

6.1 Time to Cross

We found a statistically significant main effect for the type of assistance ($F(2, 42) = 6.7, p < 0.001, \eta^2 = 0.043$). Post-hoc tests showed that participants were significantly faster in crossing decision-making at uncontrolled intersections with the X-ray ($p = 0.025$) and the Countdown ($p < 0.001$) visualizations compared to no assistance. However, we did not observe a statistically significant difference between both types of visualizations ($p > 0.05$). In addition, we observed a statistically significant main effect for traffic density. We found that bicyclists made faster crossing decisions when traffic volumes were sparse than when traffic volumes were dense ($F(1, 21) = 16.94, p < 0.001, \eta^2 = 0.11$). However, we did not observe an interaction effect between visualization type and traffic density ($F(2, 42) = 0.15, p > 0.05, \eta^2 = 0.001$) (Figure 6 left).

6.2 Accident Rate

A statistically significant main effect for the traffic density revealed that cyclists had a higher accident rate in dense than in sparse traffic flows ($F(1, 22) = 35.9, p < 0.001, \eta^2 = 0.2$). However, we did not observe a main effect for types of visualizations ($F(2, 44) = 0.6, p > 0.05, \eta^2 = 0.008$) and an interaction effect for the types of visualizations and the traffic density ($F(2, 4) = 2.8, p > 0.05, \eta^2 = 0.015$) (Figure 6 right).

6.3 Gap Selection

We observed a statistically significant main effect for the type of visualizations ($F(2, 44) = 3.75, p = 0.03, \eta^2 = 0.014$) in selecting a gap between cars. Post-hoc analyses revealed that cyclists were more successful in selecting shorter gaps with the X-ray visualization than with no assistance ($p = 0.027$). However, we did not observe statistically significant differences between the Countdown and the X-ray ($p > 0.05$) and the Countdown and no assistance ($p > 0.05$) Additionally, we observed a statistically significant main effect for the traffic density ($F(1, 22) = 261, p < 0.001, \eta^2 = 0.67$). It shows that cyclists were less successful with getting into shorter gaps between cars in the dense than in the sparse traffic flows.

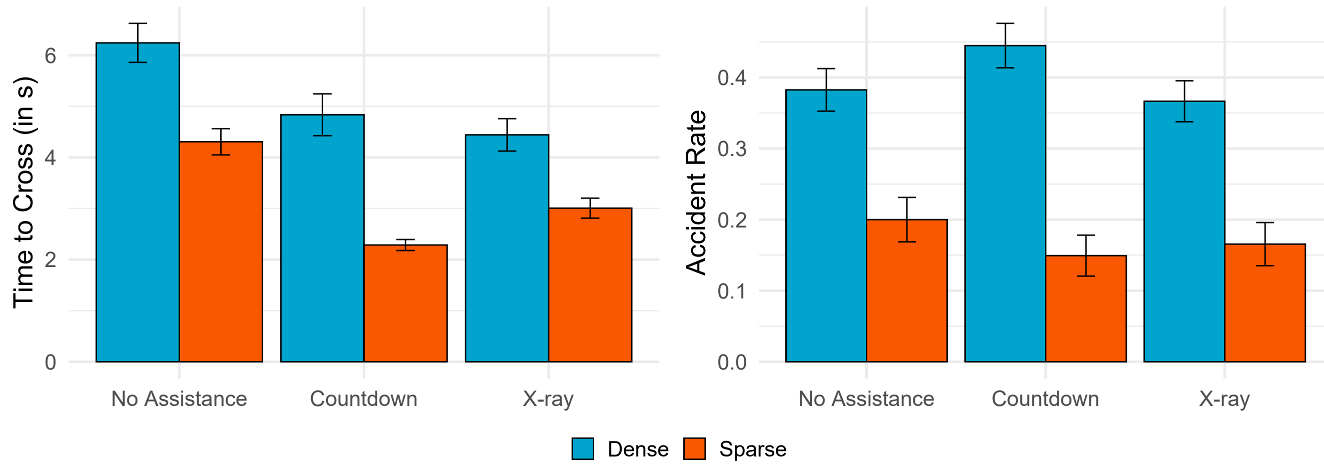

Figure 6: Overview of results: means and standard errors for time to cross (left) and accident rate (right).

There was no statistically significant interaction effect for the types of visualizations and the traffic density ($F(2, 44) = 0.42, p > 0.05, \eta^2 = 0.001$). We further looked at the frequency of selected gaps when crossing and corresponding accident rates within each selected gap, which we report in the following (Figure 7).

6.3.1 Unidirectional traffic flow. We found that most participants chose the largest available gap between cars (3.6 seconds) in dense unidirectional traffic flow for both visualizations and no assistance. The 3.6 seconds gap led to the lowest accident rate of 28% for no assistance, 47% for the Countdown, and 23% for the X-ray. However, cyclists did not choose the largest gap in the sparse traffic flow. With the Countdown visualization, cyclists chose the shortest gap of 4.5 seconds with an accident rate of 29%. The selection gap was 5.4 seconds with the X-ray and no assistance with accident rates of 14% and 23%, respectively. The larger gaps of 6.3 and 7.2 seconds were selected the least frequently for all visualizations.

6.3.2 Bidirectional traffic flow. At the intersections with the dense bidirectional traffic flow, cyclists chose a 4.5 seconds gap using the X-ray the most frequently with an accident rate of 10%. In the same situation, the selected gap for both the Countdown and no assistance is 5.4 seconds with accident rates of 11% and 22% correspondingly. In the case of the sparse traffic flow, most selected gaps were shorter with visualizations (7.2 seconds) than with no assistance (9 seconds). The accident rates in this situation lay by 10% with the Countdown and the X-ray, and by 25% with no assistance.

6.4 Minimum Distance to Cars

We observed a statistically significant main effect for the traffic density ($F(1, 22) = 64.9, p < 0.001, \eta^2 = 0.25$). It shows that the distance between a cyclist and the closest car was shorter for the dense than for the sparse traffic flows. However, we did not observe a statistically significant main effect for visualizations ($F(2, 44) = 0.6, p > 0.05, \eta^2 = 0.008$) and an interaction effect for the types of visualizations and the traffic density ($F(2, 4) = 3.1, p > 0.05, \eta^2 = 0.025$) (Figure 8 left).

6.5 Perceived workload

We observed a significant main effect for types of visualizations ($F(2, 44) = 4.96, p = 0.011, \eta^2 = 0.039$). Post-hoc tests showed that cyclists were less mentally overwhelmed using the X-ray visualization than the Countdown ($p = .03$) and no assistance ($p = 0.03$) when making crossing decisions in the dense traffic flow. However, the raw TLX values were not significantly different between the Countdown and no assistance ($p > 0.05$). Additionally, we observed a statistically significant main effect for the traffic density($F(1, 22) = 14.56, p < 0.001, \eta^2 = 0.06$). It shows that the mental load was higher when making crossing decisions in dense traffic flow than the sparse one ($p < 0.001$). However, we did not observe a significant interaction effect for types of visualization and traffic density ($F(2, 44) = 1.22, p = 0.3, \eta^2 = 0.007$) (Figure 8 right). Additionally, we found differences in traffic density for all NASA TLX metrics and in visualizations for four dimensions: Physical demand (X-ray > no assist.), Temporal demand (X-ray > Countdown), Effort (X-ray > no assist.), and Frustration (X-ray > no assist.).

6.6 Cycling behavior

According to observations during the experiment, most participants stopped when approaching intersections with traffic flows. In situations where no traffic flow was observed when approaching an intersection, cyclists either slowed down to look around or continued without changing their speed. Therefore, time to cross was considered equally for intersections where participants stopped and biked continuously across the intersection. However, we did not measure the cycling speed of participants.

6.7 Perception of safety, visual assistance, and situational awareness

6.7.1 Perception of Safety. We observed a statistically significant effect for the types of visualizations ($F(2, 115) = 3.76, p = 0.025$). Post-hoc tests showed that cyclists felt safer when crossing intersections with the Countdown ($Md = 4, IQR = 1$) than with the X-ray ($Md = 3, IQR = 2$) ($p < 0.05$). However, we did not observe

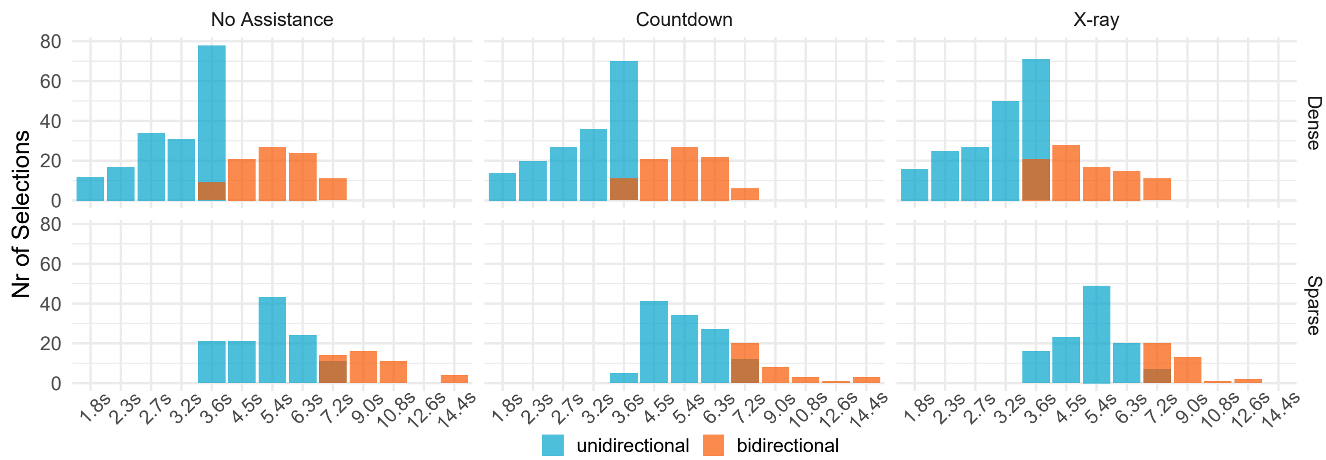

Figure 7: Overview of results: frequency of gap selection for sparse and dense traffic flows with a distinction between uni- and birectional traffic.

statistically significant differences comparing no assistance to the X-ray ($p > 0.05$) and the Countdown ($p > 0.05$) We further did not observe a statistically significant main effect for the traffic density ($F(1, 115) = 0.063, p > 0.05$) and the interaction effect for visualizations and traffic density ($F(2, 115) = 0.45, p > 0.05$) (Figure 9).

6.7.2 Visual Assistance. As for the appropriateness of the assistance, both the X-ray ($Md = 3.5, IQR = 2$) and the Countdown ($Md = 4, IQR = 1$) were rated positively. However, we did not observe statistically significant main effects for the types of visualizations ($F(2, 115) = 2.62, p = 0.07$) and traffic density ($F(1, 115) = 1.76, p = 0.18$), as well as no interaction effect for the type of visualization and the traffic density ($F(2, 115) = 0.42, p = 0.65$) (Figure 9).

6.7.3 Situational awareness. Based on the Likert scale results, the Countdown ($Md = 4, IQR = 1.5$) visualization was perceived as the best visualization to provide a good overview of the traffic situation at intersections compared to the X-ray ($Md = 3, IQR = 2$) and no assistance ($Md = 3, IQR = 2$). We observed a statistically significant main effect for the type of visualization ($F(2, 115) = 3.55, p = 0.03$). Post-hoc tests revealed that the Countdown provided a better overview than the X-ray visualization ($p = 0.05$) and no assistance ($p = 0.05$). However, we did not observe a statistically significant main effect for the traffic density and interaction effect for the type of visualization ($F(1, 115) = 0.61, p > 0.05$) and the traffic density ($F(2, 115) = 0.43, p > 0.05$) (Figure 9).

6.8 Problems and preferences

Based on the subjective post-study interview responses, we found that most participants preferred the X-ray visual assistance for crossing decision-making (N = 15). The main reasons included a good overview of the situation, easy to understand, increased perceived safety, and helps with the lack of peripheral vision. As our participants mentioned: *"I feel safer if I am more aware of my surroundings compared to the time I have to cross."* [P24, 33 years old]. *"The Countdown isn't appropriate for higher traffic situations, but the X-ray helped to get a better overview of the situation."* [P10, 16 years old]. The only problem with the X-ray mentioned by participants was that it had a limited field of view due to the technical limitations of the augmented reality glasses.

Participants who preferred the Countdown visualization method (N = 9) reported that this method felt more reliable and more appropriate for dense traffic flows. *"X-ray was only useful when I was far away from the crossing. Countdown felt more reliable."* [P5, 31 years old]. *"With the Countdown, I could estimate the traffic flow way better and felt safer. It was like a traffic light"* [P19, 20 years old]. As for the difficulties with the Countdown visualization, participants mentioned that they sometimes felt confused whether they should cross, unlike the X-ray visualization, which prepared them for the crossing beforehand.

As for the decision-making strategies, most participants mentioned that they have fully relied on the assisting visualization, especially using the Countdown. As one of the participants mentioned: *"I mostly focused on the Countdown, so it helped me a lot. I relied on it."* [P10, 16 years old]. Another one said: *"The visualizations had a very strong influence on the decision-making process, it was much easier to see the cars with the X-ray assistance system."* [P20, 23 years old]. Moreover, both visualizations helped the cyclists to make a crossing decision before reaching the intersection. For example, *"The more time I had [on the Countdown], the slower I approached the intersection. When I had less time, I usually stopped and cycled quickly afterward"* [P19, 20 years old]. *"With the X-ray, I just rolled to the intersection without braking to see whether cars were approaching."*

7 DISCUSSION AND FUTURE WORK

In general, AR-based assistance helped cyclists make fast crossing decisions at uncontrolled intersections. More specifically, the X-ray has ensured a fast selection of shorter gaps between cars and led to a lower mental load. At the same time, the Countdown facilitated a feeling of safety and provided a better intersection overview

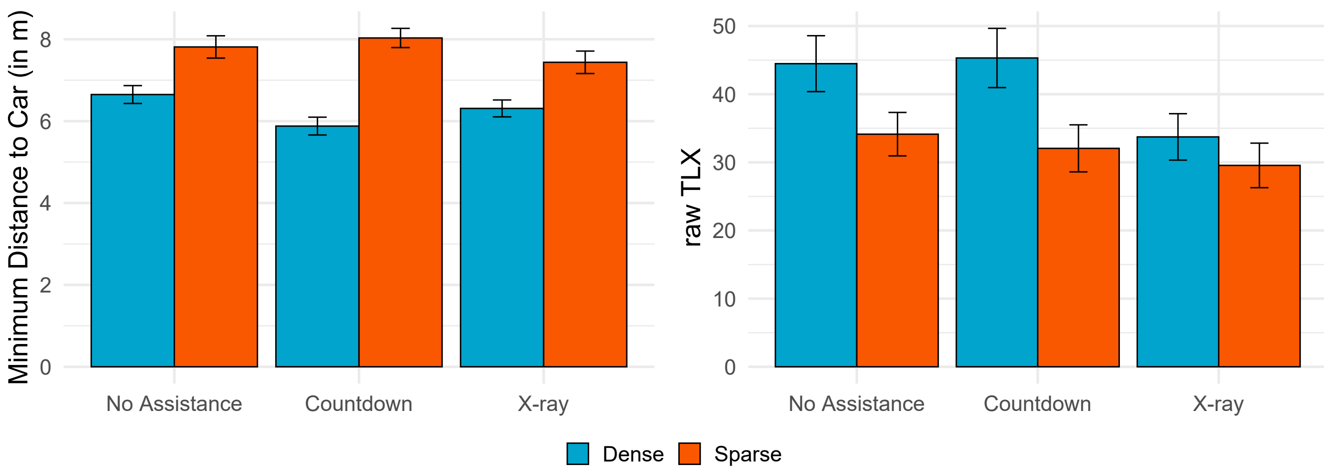

Figure 8: Overview of results: means and standard errors for minimum distance to cars (left) and perceived workload (right).

based on the Likert scale results. Moreover, we have shown that our proposed AR-based evaluation method is suitable for user studies with cyclists without limiting the natural cycling experience.

7.1 AR-based assistance for cyclists

A closer look at AR-based assistance demonstrates fundamental differences in gap selection strategies under different densities of the traffic flow. In a sparse unidirectional traffic flow, cyclists select shorter gaps using the Countdown compared to the X-ray and no assistance. On the other hand, in a bidirectional dense traffic flow, cyclists were more successful in choosing shorter gaps with the X-ray rather than the Countdown and no assistance. This indicates that both visualizations helped to understand the traffic situation at intersections better than without any assistance and facilitated crossing decisions before reaching the intersection, as supported by the qualitative results. In particular, the Countdown visualization provides a better spatial overview of the intersection upon approaching based on the quantitative data. It ensures a precise estimation of time left for safe crossing.

The estimation of time left before safe crossing leads to a higher reliance on the technology than self-estimation of the traffic situation. This facilitates a higher level of responsibility for the decision-making process. With this, the Countdown has shown better suitability for the sparse traffic flows, given its shorter duration to cross the road, lower accident rates, and longer distances to cars. The X-ray seems to be a better solution based on the same factors in situations with a dense traffic flow. Similar differences in traffic densities and directions were also previously shown for pedestrian road crossing in virtual environments [22].

As for the mental load, the X-ray was perceived as a less mentally demanding visualization compared to the Countdown, especially in a dense traffic flow. These findings are in line with previous works regarding an increased mental load while driving in dense traffic flows [47]. The observed difference can be caused by the fact that the X-ray visualization was a natural extension of cyclists' vision similar to non-occluded rural environments [60]. Given that the remaining time in the Countdown visualization employs a numeric display, it provides a more precise estimation of time compared to spatial awareness with the X-ray, which might have led to cyclists' impatience [16], a higher level of stress and, therefore, higher mental workload. The future designs of the Countdown visualization might require an abstract time representation, for example, using light [37] and color change similar to navigation [35], or integrating an abstract countdown into existing traffic infrastructure [15, 46].

7.2 Safety, confidence, and trust

Creating a feeling of *safety* for cyclists does not necessarily imply safe decision-making. As our results have shown, additional technological assistance can accelerate cyclists' crossing decisions by increasing a feeling of safety. Still, it does not necessarily lead to fewer accidents, i.e., increased road safety. However, the accident rate with visualizations remained comparable to no assistance for both traffic densities. This might be explained by an increased *confidence* of using an assisting technology, which "encouraged" cyclists to take higher risks. Moreover, the confidence in using technological interventions allowed cyclists to make fast crossing decisions and strengthen their feeling of safety. This observed imbalance between perceived (subjective) safety and quantifiable (objective) safety [34] raises important questions for future research in urban HCI: "Why is it the case?", "How can we increase both perceived and quantifiable safety?". Given the complexity of safety issues and a high number of road users, one possible reason for this imbalance can lie in the necessity of a compound solution. It should consider the whole road eco-system from many aspects, including additional cyclist training programs, reconsidering cycling infrastructure in urban environments, and additional technological interventions for all road users.

We observed that most participants have fully relied on the visualizations and made crossing decisions in advance. It was most likely caused by a high level of *trust* towards the technology. This might indicate how the constantly increasing reliability of everyday technology can neglect the need to question the possibility

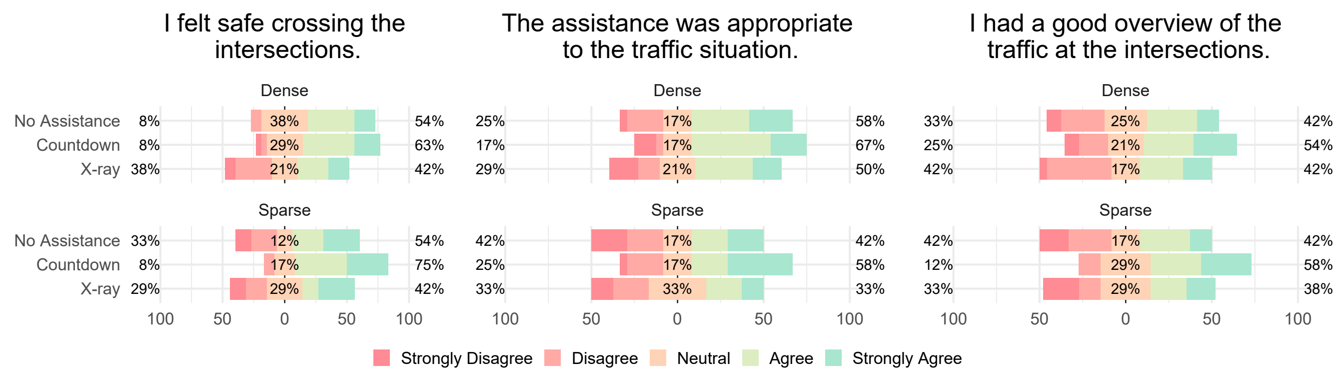

Figure 9: The participants' 5-point Likert scale ratings regarding safety, assistance, and situation awareness at intersections with dense and sparse traffic densities and two assistance systems.

of technological failures. Although all participants tried cycling with AR for the first time, they could quickly develop trust towards both visualizations already within the duration of the experiment. Higher trust for technology might increase both the potential of using it and the number of cyclists, i.e., safety in numbers [14]. However, unlike rapid trust and reliance on the assisting technology, we can observe a possible decrease in participants' trust towards the proposed experimental setup. Given that the proposed setup is a simulation, the consequences of having an accident are minor, which does not require them to be more careful, especially after a long time, which most likely led to increased accident rates, as discussed above. Therefore, we can expect that bringing such a crossing scenario to the real world without enforcement to make a crossing decision might lead to increased crossing times or participants' decline to cross at all. However, we envision that such assisting systems have the potential to reach the level of today's traffic light systems, where cyclists have an opportunity to check whether all cars stopped or blindly follow the instructions of the traffic lights.

7.3 Integration into existing cycling accessories and infrastructure

The evaluated AR visualizations can be integrated in existing cycling accessories [9] and smart infrastructures [24]. The X-ray vision can be integrated into the helmets' visors or cycling glasses, which offer a smart see-through view similar to the AR glasses. Both types of accessories are predominant mobile devices available on the market, and helmets, in particular, are mandated safety equipment in some countries.

With the development of smart city infrastructure and Car2X technology [38] supported by 5G, the Countdown visualization can be integrated into the existing traffic lights to ensure a constant bicycle flow and facilitate "green waves" without any interruptions in the busy times of the day. In this case, every digital countdown is personalized for each cyclist and provides private recommendations shown in the helmet or glasses regarding the remaining time for crossing the road safely.

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7.4 AR-based approach for conducting user studies with cyclists

Our newly proposed approach enabled us to conduct a careful and thorough indoor evaluation without limiting the natural cycling experience. With this, we aimed to increase the ecological validity of the results, given that cyclists had to balance, pedal, and coordinate their movement as in the real world, unlike previous experiments in fixed indoor bicycle [26, 30–32, 54] simulators, or on outdoor test tracks [10, 11, 31, 33] that restricted their movement and reduced cycling experience. Moreover, participants could naturally anticipate potential dangers from the real world, e.g., cycling against the wall in case of technical failures of the AR glasses, without putting themselves into danger. However, the proposed AR-based approach requires further validation to showcase its appropriateness as the evaluation method in different contexts and with other types of vulnerable road users. Although we focused specifically on cyclists in this paper, the proposed AR-method method can be effortlessly extended to outdoor test-track experiments with other road users, e.g., pedestrians, e-scooter, and car drivers, where they can walk or drive with AR glasses, respectively.

We discovered that the proposed AR-based approach has several perceptual and technical limitations. The cyclists found the Countdown visualization the most suitable when it comes to the subjective perception of safety and intersection overview. This can be explained by the fact that upon arrival at intersections, the X-ray visualization becomes comparable to no assistance in the sense of the intersection overview. On the other hand, we observed that cyclists had unrealistically high accident rates in this type of simulation compared to stationary bicycle simulators [7, 18, 40]. One possible reason for a high accident rate is that cyclists did not have a good understanding of the bicycle's length (1.8 meters) in relation to the virtual environment. This led to the situations where cyclists successfully crossed the intersection, but the back of the bicycle still was hit by a virtual car. The second reason for a high accident rate is that participants perceived the study setup as a simulation rather than a real-life experience, where a wrong crossing decision can have fatal consequences. The third reason could be that the limited physical space and setup prevented a natural buildup of cycling speed, affecting the overall crossing behavior of bicyclists.

Although participants could wait as long as they wanted to make a crossing decision, the whole process could have become tedious for them after some time, which led to higher impatience and lower risk. Unlike fixed-based cycling simulators, where cyclists had only to start pedaling to cross a road while already sitting on a bicycle, in our simulation, cyclists had to push a bicycle off with a foot, balance, and get control over steering. This could have possibly led to the difficulties of time estimation and carelessness of making crossing decisions over a longer period of time. Finally, the third reason for a high accident rate can be explained by short gaps between cars, especially in a bidirectional traffic flow. Normally, there are very few accidents within sixty minutes of cycling. Still, to see differences between the proposed AR visualizations and to systematically investigate different gap sizes, we intentionally made it too hard for participants to provoke more accidents than there usually are.

As for the technical limitations, given the limited physical space within the indoor hall, we had to make changes to the simulation, which led to a lower realism of the simulation and possibly increased accident rates due to its "miniature" look (Figure 3). However, lighting conditions play an essential role in the calibration of the augmented reality glasses, which currently restricts the experimental environments to the indoor halls or the outdoor experiments at the restricted areas in early mornings or late evenings due to visibility constraints of the virtual content. Moreover, the sun interferes with the infrared sensor of augmented reality glasses, and rainy/foggy weather might negatively influence the electronics.

8 LIMITATIONS

Although the virtual world shown in the augmented reality glasses does not precisely reflect the look of the outside world due to the limitations of the graphical capabilities, it still provides a sufficient approximation of dangerous situations. The simulation environment used in our evaluation is purely visual and did not include sounds of approaching cars, traffic, and background noises. However, creating a realistic representation of the AR-based approach for conducting user studies with cyclists has a long way to go and might require further augmentation with auditory feedback, as suggested by Stelling-Kończak [51]. The traffic flow behavior was also simulated, which might have looked unnatural. Our evaluation aimed to force cyclists to make a crossing decision and, therefore, better understand how they make a crossing decision and what kind of assistance they might require experiencing different densities of traffic flow.

Our work showed the suitability of the proposed AR-based approach for conducting experiments with cyclists, which facilities an increase of ecological validity of the results. While we recruited a diverse and broad group of participants, we acknowledge that it is hard to generalize our results to a wider group of cyclists, especially regarding culture or local traffic regulations. However, with these findings, we provide the first empirical evaluation of AR-based visualizations to assist cyclists in crossing decision-making at uncontrolled intersections using augmented reality simulation within a real-world environment.

9 CONCLUSION

In this paper, we investigated AR-based visualizations to assist cyclists by crossing decision-making at uncontrolled intersections. To evaluate both visualizations, X-ray and Countdown, we proposed a new AR-based approach for conducting user studies with cyclists to facilitate a safe, immersive, and realistic study setup. Based on the empirical evaluation, we showed that with the support of AR-based visualizations, cyclists successfully made fast road crossing decisions. Additionally, we discovered that cyclists were fast and more successful in selecting shorter gaps with the X-ray visualization while keeping the lowest accident rate. Lastly, the X-ray visualization led to a lower mental load, while the Countdown visualization ensured a feeling of safety and provided a better intersection overview based on subjective feedback.

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