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Bicycle Simulator Use to Evaluate Safety Risks and Perceptions for Enhanced Sustainable Urban Mobility

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Abstract: (1) Background: As cycling gains popularity as a mode of transportation, the frequency of accidents involving cyclists also rises. This has become a major concern for traffic safety, sustainability, and city planning. Identifying the risk factors that contribute to bicycle road accidents remains a significant challenge. This study aims to figure out which risk factors make some road segments more dangerous for cyclists than others. (2) Methods: This study introduces the use of a bicycle simulator to test different road segments involving thirty-nine participants. The impact of demographics and some risk factors related to infrastructure were analyzed in terms of their influence on the perceived level of risk through pre- and post-surveys. (3) Results: The findings showed that the bicycle facility type affects the perceived level of risk. Shared-use roads were ranked as riskiest, while separated bike lanes were least risky. Bicycle roads with no separated safety barriers had higher risks. Heavy traffic jams increased danger among cyclists. Women gave higher risk ratings than men. The perceived levels of risk were then compared with the previously developed risk index and they correlated well. (4) Conclusions: This confirms that the risk index can reliably evaluate the degree of risk of each road segment.

Keywords: risk factors; users' experience; bicycle simulator; perceived risk; sustainability mobility modes

Citation: Ayad, L.; Imine, H.; De Crescenzio, F.; Lantieri, C. Bicycle Simulator Use to Evaluate Safety Risks and Perceptions for Enhanced Sustainable Urban Mobility. *Sustainability* **2024**, *16*, 9786. https://doi.org/10.3390/su16229786

Academic Editors: Maria Vittoria Corazza, Béatrice Cahour and Sonia Adelé

Received: 2 September 2024
Revised: 16 October 2024
Accepted: 6 November 2024
Published: 9 November 2024

1. Introduction

An increasing number of people are using bicycles around the world for different reasons, whether it is for commuting, exercise, cost-saving measures in this inflation period, or aligning with green initiatives put in place by countries. This cycling boom has encouraged governments to prioritize bicycle-related safety measures, recognizing both the environmental benefits and the need to protect cyclists on the roads. Initiatives range from infrastructure improvements to legislative actions aimed at reducing fatalities and injuries. However, cyclists are still classified as vulnerable road users, with higher accident risks of accidents than other road users [1].

The statistics show how much cycling has grown worldwide. In the United States, the number of cyclists increased from 47.5 million in 2017 to more than 52.7 million in 2020 [2]. Moreover, in Great Britain, bicycle traffic witnessed a remarkable 96% growth, with a 26% increase in average riding trips in the same year [3]. European countries have seen a significant increase in the number of cyclists, with approximately 41 million persons relying on bicycles as their main means of transportation in 2020 [4].

On the other hand, cyclists are often vulnerable road users and frequently involved in traffic-related injuries and fatalities. For example, in the UK, serious injuries among cyclists increased by 26% in 2020 [3]. France, despite its efforts to promote bicycle use, recorded an increase in bicycle fatalities in 2019. It recorded the highest number of bicycle-related deaths, with 187 persons losing their lives, as reported by [4]. Correspondingly, Germany experienced a rise in fatalities, with 445 deaths recorded in 2019, reflecting a 4.6% increase from 2010 [5].

The increase in bicycle accidents emphasizes how safety measures are urgently needed to protect cyclists on the roads. Therefore, it becomes important to conduct an in-depth identification and analysis of different risk factors related to bicycle accidents. Previous research studies have mainly focused on evaluating these risk factors through accident data analysis, traditional surveys, bicycle simulator experiments, and direct real-road observations. These studies have identified many factors, including infrastructure conditions and cyclist behavior, as significant contributors to the occurrence of bicycle accidents. It has been identified that risky cyclist behavior, such as traffic violations or distractions, is a major factor in 40% of accidents involving cyclists [6]. Moreover, there are a number of risk factors that worsen the complexity of bicycle accidents, such as the presence of obstacles, interactions with other road users, and poor infrastructure conditions.

Furthermore, our previous research study has developed a risk index formula to analyze the contributory risk factors to bicycle accidents. This index includes nineteen factors, categorized into facility features, infrastructure characteristics, cyclists' behavior and demographics, and weather/traffic conditions. These factors were weighted to evaluate their relative importance using a risk matrix and an Analytic Hierarchy Process (AHP). The risk index (RI) can be used to evaluate the conditions of roadway segments. By considering the presence and frequency of different risk factors within a given road segment, the RI provides a quantitative measure of the level of risk to cyclists [7]. This approach enables policy-makers to make decisions regarding infrastructure improvements and safety interventions aimed at enhancing cyclist safety.

Therefore, one of the goals of the current study is to conduct simulations using a bicycle simulator to evaluate the risk index developed in our previous research. Participants were immersed in virtual environments with different infrastructure conditions and interactions with other road users. Then, participants provided their perceived levels of risk and the influence of contributory risk factors through post-simulation survey questionnaires.

1.1. Previous Research On-Road Assessment for Cyclists

Previous research has evaluated cyclists' roads, focusing on specific aspects such as safety and comfort by either using traditional surveys or bicycle simulators. They have identified different criteria impacting cyclists, including factors such as perceived safety, stress levels, and comfort. For example, ref. [8] emphasizes the significance of perceived safety in influencing cyclists' behavior and route choices, while ref. [9] highlights how stress and comfort shape overall cycling experiences. Moreover, ref. [10] identifies factors like road conditions and traffic density as essential in shaping cyclists' perceptions and behaviors.

An innovative advance in this field is the SafeCycling system introduced in [11], which uses geospatial data and GPS coordinates to evaluate real-time risk levels for cyclists and send alerts when they approach high-risk zones. This system aligns with smart cities' initiatives, the Internet of Things (IoT), and open data use in urban environments. Furthermore, ref. [12] presents a geospatial assessment methodology for evaluating the risk of cyclist accidents in urban areas by integrating data on road intersections, bike lanes, and bus stops. This study identifies distinct risk clusters within cities by integrating K-means clustering. The experimental results from Munster, Germany validate the effectiveness of this data-driven methodology in promoting sustainable smart cities by defining high-risk locations.

In contrast, some studies, like [13], used surveys to evaluate perceived cycling safety in different locations, aiming to enhance bicycle road facilities. Another study investigates how a microenvironment design on bicycle streets affects cyclists' perceived safety. Using a quasi-experimental survey approach, it finds that features like red-colored bicycle lanes and reduced traffic volume significantly improve perceived safety [14]. However, traditional surveys may not always reflect cyclists' real-life psychological responses, leading to potential misinterpretations [15]. A recent study [16] highlights the value of using surveys in assessing perceived cycling safety and identifying unreported crash incidents, which can significantly impact infrastructure decisions. This survey analysis has identified that a large number of crashes go unreported to police authorities, leading to potential misidentifications of crash hotspots by urban planners. The study has found that while cyclists perceive overtaking and lane-changing as dangerous, the most common crashes are single-vehicle incidents, often due to unexpected hazards such as distraction, road conditions, and unfamiliar routes.

Bicycle simulators have also contributed significantly to understanding cyclists' safety in virtual environments. For example, a study by [17] has used a bicycle simulator to determine the optimal pavement markings for bicycle wayfinding and suitable cyclist positioning at signalized intersections. Similar to this, a different study examined the effects of bicycle wayfinding signage on participant safety, identifying that signage with a green circle had better visibility in delineating bicycle routes [18]. In a different approach, a study by [19] has integrated a bicycle simulator with immersive virtual reality (VR) to investigate the impact of different cycling environments, traffic volumes, and pedestrian presence on perceived safety levels. Their findings have indicated that participants expressed greater confidence in cycling on segregated bicycle paths compared to painted bicycle lanes on the road or along the roadside. Furthermore, ref. [20] has used a bicycle simulator within an immersive virtual environment (IVE) to analyze cyclists' behavioral and physiological responses. The study has shown that the design of protected bike lanes resulted in the highest perceived safety rating and led to decreased average cycling speeds. There are differences in how men and women perceive safety while cycling. Female participants tended to feel safer in protected bike lanes and rated the shared lanes as less safe. This aligns with previous research showing that women prefer more separation from motor traffic. Women perceive higher levels of risk which could affect their willingness to ride. This highlights the importance of protected bike lanes in encouraging more women to cycle [20].

Lastly, a study by [21] showed how older cyclists, who accounted for 69% of fatal bicycle accidents in Japan in 2021, react in a dangerous traffic situation using a simulator integrated with VR technology. The results show that older participants are less accurate when it comes to following safe routes and are more prone to accidents due to factors such as poor rear-end checking, delayed decision-making, and reduced operational ability.

These studies have used different methodologies to evaluate and improve the safety of cyclists in urban environments, as the field of cycling safety studies continues to develop. The approaches applied range from traditional surveys and bicycle simulators to geospatial assessments and innovative real-time risk evaluation systems. Table 1 summarizes the findings and the approaches reviewed in this section to evaluate cycling safety and infrastructure design. This table presents a basis for the current research to identify the opportunities in the field of cycling safety.

Table 1. Comparative analysis of literature on cycling safety.

Study	Year	Methodology	Key Findings	Relevance to Current Work
[8,9,13]	2018,2021,2022	Surveys	Highlights the importance of perceived safety, stress, and comfort as key factors that influence cyclists' behavior and route choices.	Provides foundational understanding of cyclist perceptions, essential for evaluating cycling safety.
[14]	2021	Quasi-experimental survey	Studies how the design of microenvironments affects cyclists' perceived safety on bicycle streets.	Offers evidence on design features that can make cyclists feel safer.
[15]	2022	Surveys	Highlights the limitations of traditional surveys in identifying cyclists' psychological responses.	Suggests the need for more nuanced methods in assessing cycling safety.

Table 1. *Cont.*

Study	Year	Methodology	Key Findings	Relevance to Current Work
[16]	2023	Surveys	Identifies that unreported crashes can influence infrastructure decisions by shedding light on cyclists' experiences.	Indicates gaps in data reporting that can affect urban planning for cycling safety.
[10]	2022	Mixed Methods	Studies the effects of road conditions, traffic density, and available amenities on cyclists' perceptions and behaviors.	Helps to improve safety measures.
[11]	2023	Geospatial Data	Introduces the SafeCycling system, which uses geospatial data and GPS for real-time risk assessment and alerts.	Provides a practical framework for current risk assessment methodologies.
[12]	2023	K-means Clustering	Uses geospatial assessment to identify distinct risk clusters for cyclist accidents in urban areas.	Provides a methodological basis for identifying high-risk areas relevant to urban planning initiatives.
[17,18]	2022,2021	Bicycle Simulator	Studies optimal pavement markings for wayfinding and cyclist positioning at intersections and their effects on perceived level of safety.	Provides infrastructure designs that enhance cyclist safety.
[19]	2023	Bicycle Simulator with VR	Integrates VR to examine how different cycling environments impact perceived safety levels.	Provides infrastructure designs that enhance cyclist safety.
[20]	2023	IVE with Simulator	Analyzes how cyclists behave in protected bike lanes.	Provides analysis on cyclist behavior.
[21]	2022	Bicycle Simulator with VR	Studies the behavior of cyclists in risky traffic situations.	Helps to develop strategies to enhance safety for cyclists.

1.2. Research Gaps and Objectives

Previous studies have been conducted to evaluate cyclist safety through traditional surveys and bicycle simulators and have made significant contributions to the field of cyclist safety. Most studies either rely on perceived risk assessments or analyze single environmental factors. For example, previous surveys were used to analyze perceived safety but might miss actual risk influences from specific road or traffic conditions. Similarly, previous studies using bicycle simulators lack detailed analyses of different risk factors. Moreover, their use in understanding the correlation between perceived risk and actual risk indices remains limited.

On the other hand, current methodologies, like the SafeCycling system, highlight real-time risk evaluation based on geospatial data, but these systems focus on objective measurements without integrating participant perceptions across different demographics.

One of the aforementioned gaps was filled in our previous work by identifying risk factors and introducing a risk index to evaluate the risk level for cyclists in different road conditions. The results and a detailed procedure are available in [7]. This index quantifies the relative importance of nineteen factors related to infrastructure features, cyclist behavior, and traffic/weather conditions using a risk matrix and the Analytic Hierarchy Process (AHP).

The current goal is to fill these gaps using an immersive bicycle simulator combined with surveys. The simulator provides a near-realistic environment where participants face several road conditions. In this paper, the bicycle simulator was integrated with the survey method to question participants about their evaluation of each road environment and corresponding risk factors, such as the presence of obstacles, the absence of safety barriers, and the presence of access points.

Thus, the objectives of this study are as follows: first, the examination of risk perceptions of different environments and traffic conditions; second, the higher risk factor impacting the risk perceptions; and third, the influence of demographic differences on cyclists' risk perceptions. This study aims at comparatively studying the correlation between the risk index developed and the perceived level of risk.

The immersive nature of the simulator improves the realism of the experiment, which allows for a detailed examination of risk perception across different infrastructure conditions. While the reliability of the simulator was evaluated through simulator sickness measures, the main focus of this study remains on evaluating perceived risk in various scenarios with different traffic levels and how these perceptions correlate with both demographic factors and the previously developed risk index.

The flexibility of the bicycle simulator also allows for integration with surveys or interviews, which facilitates an in-depth analysis of the study's research questions. The bicycle simulator is a practical tool for examining infrastructure scenarios and collecting demographic data to evaluate its influence on cyclists' perceptions.

Therefore, this study aims to address the following key research questions:

- How do cyclists perceive levels of risk in different types of facilities across varying traffic conditions?
    - ○ How do variations in traffic volume influence cyclists' perceived risks in these scenarios?
- How do perceived levels of risk compare with the calculated risk index across different road segments?
- What risk factors significantly impact cyclists' perceived level of risk?
- How do demographic variables such as age, gender, and bicycle level of experience affect perceptions of risk, and how do men and women differ in their risk perceptions?
    - ○ What are the differences between male and female cyclists regarding their perceptions of risk?

2. Materials and Methods

2.1. Bicycle Simulator

The study was conducted using the PICS-L bicycle simulator, located at the University of Gustave Eiffel in France, as shown in Figure 1. Developed by the French Institute of Science and Technology for Transport, Development, and Networks (IFSTTAR), the PICS-L bicycle simulator is built by placing a real bicycle on a platform with a degree of freedom (DOF) for the steering angle. Five visual screens in front and on the sides of the bicycle provide the forward view with a visual angle of 225 degrees horizontally and 55 degrees vertically. An additional display behind the left shoulder provides a rear visualization of the road. Ambient sounds around the bicycle are modeled with a surround sound system.

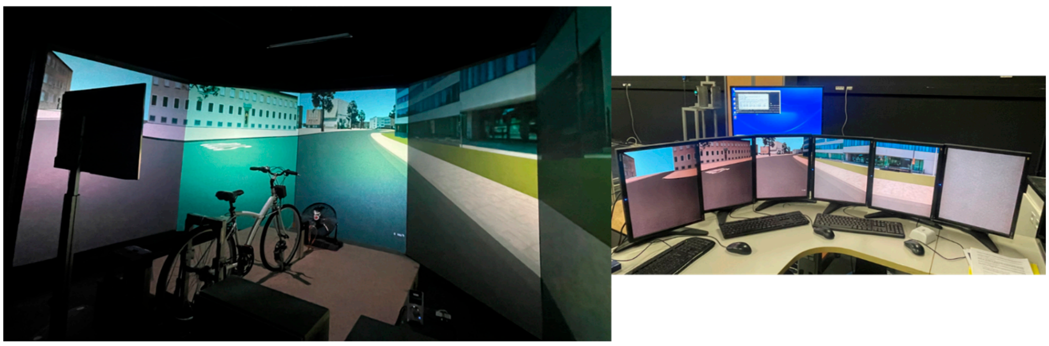


Figure 1. Bicycle simulator (**left**) and operator workstation (**right**).

Realistic circumstances are provided by several components:

- A front-mounted fan reproduces airflow, representing real-life cycling situations. The fan speed is proportional to the rear wheel's speed.
- An incremental encoder on the fork enables rider interaction with the virtual environment. It provides realistic haptic force feedback to the handlebar and also measures the steering angle and velocity.
- A passive mechanical lateral suspension system allows participants to tilt the bicycle slightly when turning left or right.
- A flywheel, connected to the rear wheel, simulates inertia equivalent to 60 kg of mass in real cycling. The simulator includes a motor that can increase the inertia up to 85 kg as in real cycling conditions.
- An incremental encoder, attached to the rear wheel, calculates the speed of the bicycle and provides input to virtual reality to determine the cyclist's position and trajectory.
- The simulator features five visual displays forming a cave virtual environment in front and on the sides of the bicycle. This provides a visual angle of 225 degrees horizontally and 55 degrees vertically to improve immersion. An additional display behind the left shoulder provides a rear visualization of the road.
- Three actuators, installed on the platform, replicate vibrations induced by uneven road surfaces. The acceleration is limited to ± 1 g to maintain platform stability, with an amplitude limitation of ± 2.5 mm (extendable up to ± 5 mm) at frequencies ranging from 10 Hz to 20 Hz.
- A cylindrical asphalt specimen, introduced to replace a plastic cylinder, interfaces with the rear tire to simulate road adhesion. The specimen consists of hot-mix asphalt concrete and has a diameter of 10 cm and a height of 12 cm. A central penetration allows a 2 cm diameter shaft to pass along its axis for secure fixation.

The simulator runs with the MATLAB dynamic model, integrating a six-degree freedom framework (longitudinal, lateral, vertical, yaw, pitch, and roll). Participants can be monitored from the operator's workstation located at the rear of the bicycle simulator, as shown in Figure 1.

In the simulation, accidents are impossible since the participants can pass through obstacles and other drivers without any risk of collisions. This is communicated to all participants.

Importantly, this bicycle simulator was validated in a previous study that compared some performance measures of participants riding on the road and riding in the simulator. The results of this validation study confirmed the relative validity of the simulator across several spatial measures for different cyclists, such as speed, lateral and longitudinal acceleration, roll, yaw, and steering angle [22]. The validation of the bicycle simulator enhances the credibility and reliability of this study's findings.

2.2. Scene Development and Design

The virtual scene was built using two software tools: RoadRunner and ArchiSim. RoadRunner facilitated the creation of realistic road networks and the simulation of traffic scenarios. The layout of roads in the virtual environment replicated the actual road layout of Stockholm, where participants had previously ridden an instrumented bicycle in real-world conditions. Traffic conditions were defined to mirror different scenarios participants encountered during the experiment. Several sensors were installed on the real instrumented bicycle to enhance the realism of the simulation. A GPS sensor was used to track the participants' location and a laser scanner was used to map the terrain and surroundings to ensure an accurate representation of the real environment. In addition, participants wore eye tracking to record the environmental landscape. These sensors ensured an accurate representation of the real environment to ensure the achievement of high fidelity in the simulation. The data collected from these sensors allowed for the creation of a highly realistic virtual environment. ArchiSim was used to enhance the overall design of the virtual environment by integrating architectural features, landscapes, and environmental spaces. This included accurately modeling road profiles and intersection layouts to simulate true cycling experiences. Intersection modeling included replicating different traffic signal configurations and lane markings to imitate real-world conditions. This approach contributed to the development of a similar real environment. The integration of these sensors and software tools led to the development of a highly immersive virtual environment that directly impacts the study's fidelity.

The road layout consisted of several road segments with a total length of 1.4 km. Participants traversed three distinct road segments, each representing three different facility types. These segments included a medium volume of vehicles and pedestrian traffic. Simulated vehicles included cars only, excluding heavy motor vehicles such as buses or trucks.

The scenarios developed included different types of facilities and circumstances: shared-use road, bike lane, and bike path, all interconnected with one scene. A dedicated traffic light specifically for cyclists facilitates the merge into the bicycle lane, while another traffic light positioned at the end of the bicycle lane orders separate movements for vehicles and cyclists. Vehicles could go straight ahead, while cyclists had to turn left from a bike lane to the right to access the bicycle path. Each scenario presented different potential reactions faced by participants. They were expected to stop at different points with a red-light signal. Participants rode the bicycle lane alongside another cyclist and encountered a wheelchair user at an uncontrolled crosswalk.

The simulator validated performance measures, the realistic road network, the replication of actual traffic conditions, and the detailed modeling of environmental features. Therefore, the virtual cycling experience can be considered to accurately reproduce real-world conditions. This high fidelity and realism are essential to achieve the study's objectives and to evaluate the cyclists' perceived level of risk in different scenarios.

Detailed specifications for each scenario are outlined in Table 2 and are designed as follows:

Table 2. Overview of scenario representation, types, and descriptions.

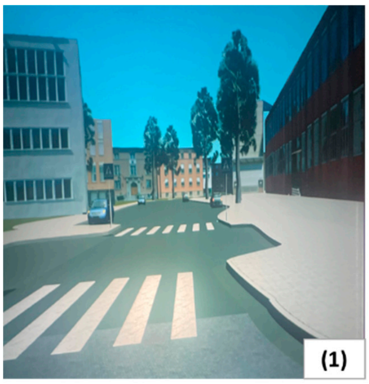
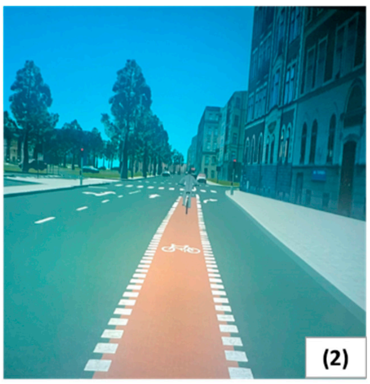
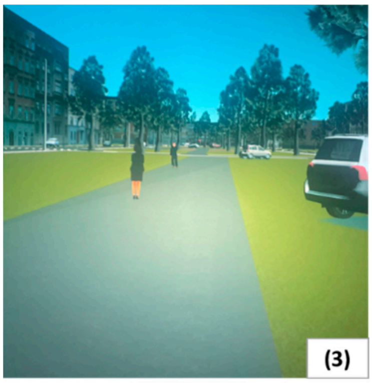
Scenario Representation	**Scenario Type**	**Scenario Description**
	Scenario 1: shared road	This road consisted of two vehicle lanes. It was designed to accommodate different road users, such as cars, motorcycles, and bicycles, all within the same roadway. The simulated distance was around 400 m and 7 m in width. The traffic condition was moderate. In this scenario, participants interacted with other vehicles that were sharing the same road.
	Scenario 2: bicycle lane	A separate bicycle lane runs parallel to the flow of vehicle traffic without physical safety barriers. The simulated distance is around 500 m in length and 1.7 m in width. The traffic condition was moderate. This scenario allowed us to examine the participant's behavior with vehicles, other road users crossing, and adherence to traffic lights.

Table 2. *Cont.*

Scenario Representation	Scenario Type	Scenario Description
	Scenario 3: bicycle path	An off-street bike path was shared with pedestrians. The simulated distance was around 500 m in length and 5 m in width. This scenario allowed us to reflect on the challenges of sharing a dedicated pathway with pedestrians.

2.3. Experiment Process

Participants were recruited through multiple methods, such as the University of Gustave Eiffel departments' email list, PhD group networks, and an existing pool of participants. The participant pool consisted of participants who had previously taken part in another study at the department and had given consent to be considered for future research. Participation was entirely voluntary and participants agreed to take part in the study.

The experimental process included different steps, each designed to finalize the experiment successfully and to collect data on perceived level of risk and factors impact. Descriptions of each step are presented in detail below:

- Bicycle simulator setup: Before the participants arrive, the bicycle simulator equipment is set up and calibrated to ensure an accurate simulation. This involves checking and adjusting the saddle height and handlebar position of the bicycle. Once the participants were ready, the virtual scene was launched on the mounted screen of the simulator.
- Orientation session: The participants were welcomed and informed about the objectives and procedures of the study. Emphasis was placed on their right to withdraw from participation at any time they felt uncomfortable or experienced motion sickness, assuring them that they would not face any disadvantages for such decisions. Before the start of the experiment, all participants willingly agreed to participate and confirmed their understanding of data privacy protocols.
- Trial ride: The participants went through a detailed introduction that included a familiarization ride on how to use the simulator. The purpose of this trial ride was to familiarize participants with handling, steering, pedaling, and braking bicycles in a virtual environment. The scenario included traffic, intersections and turns. This guarantees that the participants could familiarize themselves with the functions of the simulator and have complete control over it. Participants were given the option to extend the familiarization ride until they felt comfortable with the simulator.
- Pre-survey questionnaire: This questionnaire included questions on demographics, mobility habits, previous accident history, and contributory risk factors. While participants were asked to fill out this questionnaire, the real scenario of the experiment was launched in parallel.
- Experiment riding: Participants started to ride the actual riding scenarios, and it lasted approximately eight minutes. They faced different access points and interactions with other road users, as mentioned in the previous section. Using the bicycle model, all bicycle movements—including steering, speed, and distance—were recorded and computed during these steps.
- Post-survey questionnaires: Following the experiment, participants were then asked to complete different assessments:

- Simulation sickness questionnaire: This questionnaire aimed to measure participants' experiences of simulation sickness during the experiment. It is a self-reported symptom checklist that includes sixteen symptoms associated with simulator discomfort [23].
- Post-survey questionnaire: This questionnaire aimed to collect their risk perceptions of scenarios and identify influential risk factors. Questions in this survey were structured as Likert scale questions, allowing participants to rate their responses on a 5-point scale.
- Safety and behavior features questionnaire: This questionnaire focused on participants' safety measures and behaviors shown, both within the simulation and in real-life riding situations. Questions were designed as Likert scale questions, allowing participants to rate their safety and behavior features on a 5-point scale.
- NASA TLX load: This questionnaire aimed to assess the subjective workload felt by participants performing simulations [24].

- Monitoring and support: Throughout the experiment and survey questionnaire completion, participants' progress was monitored and assistance was provided as needed.

The combination of the pre-survey, post-survey, simulation sickness, and safety and behavior features questionnaires forms an integrated approach to understanding participants' experiences and perspectives in cycling scenarios. The pre-survey provided a baseline for collecting data on participants' characteristics before they engaged in the virtual main session. The post-survey measured the influence of the virtual environments on participants' perceptions of risk. The simulation sickness questionnaire led to understanding the different effects on the participant's overall experience. Finally, the questionnaire on safety and behavior features' offered information on participants' safety perspectives while riding a bicycle. This multi-faceted approach ensures a complete assessment that is in line with participants' experiences and concerns in different scenarios.

The pre-survey questionnaire, simulator sickness questionnaire (SSQ), and post-survey questionnaire analysis are presented in this paper.

2.4. Data Collection

A total of 39 volunteer participants (17 females) completed the bicycle simulator experiment, with the majority falling between the ages of 26 and 49 (51%). There were no dropouts due to motion sickness, indicating successful completion of the experiment without adverse effects.

The data collection process involved several steps to ensure the accuracy and reliability of the collected data.

1. Data acquisition: Data were collected through Google Forms and extracted into Excel sheets for further analysis.
2. Quality control and assurance: A quality control procedure was conducted to review the collected data to ensure its accuracy and suitability for analysis. This phase verified the completeness and appropriateness of all participant data.
3. Data analysis: R software (Version 4.3.2) was used for data analysis.
4. Statistical analyses: Different statistical analyses were applied to examine the perceived level of risk in different cycling scenarios:
    - One-way analyses of variance (ANOVAs) were used with facility type as a risk factor to evaluate the perceived level of risk across different scenarios [19,25–27].
    - Post hoc Tukey's honestly significant difference (HSD) tests were conducted for pairwise comparisons to identify the riskiest scenario [19,25].
    - Separate *t*-tests were used to analyze the effect of traffic volume, considering medium and high traffic conditions as two variables [28,29].
    - A Friedman statistical test was conducted to evaluate the important impact of risk factors on perceived risk levels [30,31].

- Mean and standard deviation values for demographic variables such as gender, age, and bicycle experience level were obtained to investigate their impacts on the perceived level of risk.

3. Results

3.1. Pre-Experiment Survey

3.1.1. Participants Overview

Table 3 outlines an overview of the sociodemographic characteristics of the participants in this study. The table is divided into four main categories: age distribution, cycling frequency as a mode of transportation, major purpose of bike riding trips, and the occurrence of previous bicycle accidents. The distribution is presented separately for males, females, and the total participant count.

Table 3. Sociodemographic characteristics of the participants.

	Males (N = 22)		**Females (N = 17)**		**Total (N = 39)**	
	Frequency	**Percentage**	**Frequency**	**Percentage**	**Frequency**	**Percentage**
Age						
18–25	7	32%	8	47%	15	38%
26–49	11	50%	9	53%	20	51%
50–64	4	18%	0	0%	4	10%
Cycling frequency as a mode of transportation						
Less Often (<Monthly)	10	45%	8	47%	18	46%
Monthly	6	27%	3	18%	9	23%
Weekly	3	14%	4	23%	7	18%
2–4 Times a Week	-	-	2	12%	2	5%
Daily or Almost Daily	3	14%	-	-	3	8%
The major purpose of a bike riding trip						
Commute to Work or University	3	14%	1	6%	4	10%
Commute for Short Distances (Shopping/Coffee Shops/etc.)	5	23%	3	18%	8	21%
Leisure and Enjoyment	10	45%	12	55%	22	56%
Exercising and Fitness	3	14%	1	6%	4	10%
Accompaniment	1	5%			1	3%
Previous Bicycle Accidents' Occurrence						
1–3 Times	9	41%	3	18%	12	32%
3–6 Times	1	5%			1	3%

Participants were grouped into three age categories, with the majority (51%) being in the 26–49 age group. In terms of cycling frequency, 46% reported cycling less than monthly, while 8% cycled daily or almost daily. The most common reason for cycling was leisure and enjoyment (56%), followed by commuting for short distances (21%). Furthermore, 32% of participants reported having experienced one to three bicycle accidents.

3.1.2. Previous Bicycle Accident Details

This section presents specific details of participants' experience of previous bicycle accidents. Participants were asked five questions to understand the circumstances of these accidents. These questions were focused on the timing of the accidents, types of bicycle accidents, the main factors contributing to the occurrence of bicycle accidents, and whether participants were injured in the accidents.

Of the 13 participants involved in bicycle accidents, the majority (92%) reported that these occurred during the day. Most of the participants who experienced accidents were male (77%). The most common type of accident was loss of control and falling (53%), followed by collisions with vehicles (29%) and pedestrians (12%). A small number of accidents (6%) were due to car dooring. (See Figure 2).

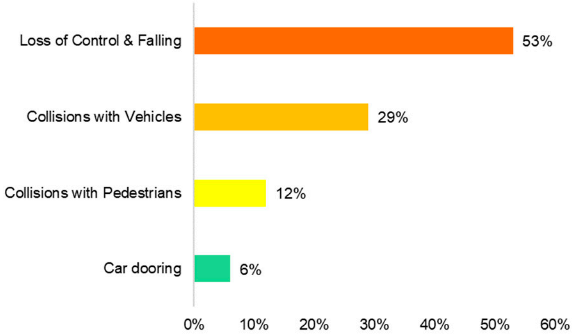


Figure 2. Bicycle accidents types.

Participants were asked about the factors that contributed to their bicycle accidents. Participants were allowed to select multiple options. Before responding, the participants were briefly introduced to what infrastructure includes, such as road width, road layout, obstacle existence, absence of vertical signs/horizontal signs, absence of safety barriers, and slope existence (downhill/uphill). According to the results, 26% of participants selected that infrastructure types had an impact on their accidents. An equal percentage, 26% of participants, were involved in accidents due to their distractions. Additionally, 15% more participants were involved in driving at high speeds, either by themselves or by other drivers. Furthermore, 11% of participants reported that they had been involved in accidents due to weather conditions, and another 11% said that high traffic volume played a role in their accidents. Small percentages were reported for disobeying traffic rules (7%) and alcohol consumption (4%).

Participants were asked about the injuries they experienced during their bicycle accidents. The purpose of this question was to evaluate the severity of these accidents. Injuries range from none, indicating no impact on their safety, to major, indicating that the risk can lead to fatal accidents. Minor injuries are shallow wounds causing discomfort and requiring basic first aid. Moderate injuries are fractures that may require medical care. Severe injuries include major conditions such as head injuries requiring hospitalization. According to the results as shown in Figure 3, 46% of participants reported having minor injuries as a result of bicycle accidents. Another 23% of participants indicated that the accidents had not injured them. Furthermore, 16% reported moderate injuries and 15% reported severe injuries.

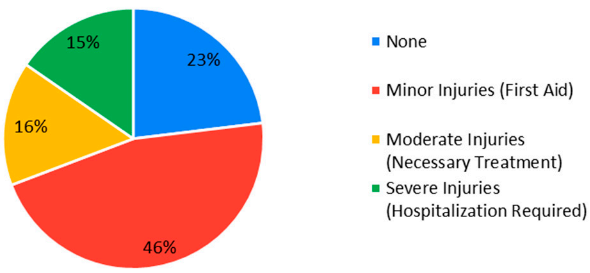


Figure 3. Types of injuries.

3.2. Post-Experiment Survey—Simulator Sickness

Simulator sickness (SS) is a problem that arises from using a virtual environment in a simulation; however, it offers a safer option for on-road research by removing the risks involved with real-world accidents. Similar to motion sickness (MS), this condition can cause symptoms like headache, nausea, dizziness, sweating, and headache. In virtual worlds, the disparity between visual perception and other sensory inputs can cause discomfort for a considerable number of people.

The most popular method for evaluating the simulator sickness is the simulator sickness questionnaire (SSQ) [23]. The SSQ is a self-reported symptom checklist, including sixteen symptoms that participants rate on a four-point scale, ranging from no symptoms to severe symptoms. Factor analysis was used to categorize these symptoms into three main parts: nausea-related subscore (N), oculomotor-related subscore (O), disorientation-related subscore (D) [23]. Weights are assigned to each category, and their sum produces a total score (TS). This total score represents the overall severity of motion sickness experienced by participants in virtual environment systems. Each category includes the following symptoms:

- Nausea-related subscore (N) includes stomach discomfort, salivation, sweating, and feeling warm.
- Oculomotor-related subscore (O) includes blurred vision, difficulty focusing, and increased salivation.
- Disorientation-related subscore includes dizziness, headache, difficulty concentrating, and yawning.

Table 4 presents the mean weights that were assigned to each symptom within a given category. Understanding the absolute magnitude of scores is supported by the mean values. The cells highlighted in gray indicate that the symptoms mentioned inside them do not fall under the corresponding category. With the greatest mean and standard deviation, the oculomotor category shows greater variability and a greater number of reported symptoms. The nausea category, on the other hand, has a higher standard deviation but a lower mean, indicating variation in the symptoms that people describe. These findings suggest that the overall symptom levels were within acceptable ranges, even though some discomfort was reported. This validates the use of the bicycle simulator for this study by providing a safe environment without introducing physiological discomfort that might affect the results of risk perception analysis.

Table 4. SSQ symptoms weight.

Symptoms	Weight	Nausea	Oculomotor	Disorientation
General Discomfort	Mean	0.62	0.62	
	Standard Deviation	3.79	3.79	
Fatigue	Mean		0.49	
	Standard Deviation		3	
Headache	Mean		0.31	
	Standard Deviation		1.9	
Eye Strain	Mean		0.49	
	Standard Deviation		3	
Difficulty Focusing	Mean		0.41	0.41
	Standard Deviation		2.53	2.53
Increased Salivation	Mean	0.08		
	Standard Deviation	0.047		
Sweating	Mean	0.21		
	Standard Deviation	1.26		
Nausea	Mean	0.28		0.28
	Standard Deviation	1.74		1.74
Difficulty Concentrating	Mean	0.18	0.18	
	Standard Deviation	1.11	1.11	
Fullness of Head	Mean			0.05
	Standard Deviation			0.32
Blurred Vision	Mean		0.18	0.18
	Standard Deviation		1.11	1.11

Table 4. *Cont.*

Symptoms	Weight	Nausea	Oculomotor	Disorientation
Dizziness (Eyes Open)	Mean			0.31
	Standard Deviation			1.9
Dizziness (Eyes Closed)	Mean			0.08
	Standard Deviation			0.47
Vertigo	Mean			0.08
	Standard Deviation			0.47
Stomach Awareness	Mean	0.08		
	Standard Deviation	0.47		
Burping	Mean	0.05		
	Standard Deviation	0.32		
Total	Mean	**1.49**	**2.67**	**1.38**
	Standard Deviation	**9.17**	**16.44**	**8.54**

3.3. Perceived Level of Risk

3.3.1. Scenarios' Rating and Ranking

Participants were asked to evaluate their overall perceived level of risk for the three scenarios upon finishing the experiment on the bicycle simulator, ranging from very low to very high. They were also asked to classify the scenarios from the least risky to the riskiest. The aim is to evaluate how variations in road conditions, characterized by different risk factors, can influence participants' perceived level of risk. The mean and standard deviation (SD) values for the perceived level of risk in each scenario are presented in Table 5. Participants reported a higher mean perceived level of risk value for cycling on the shared-use road with other vehicles (Mean = 3.77, SD = 1.07). The lowest mean perceived level of risk was reported for cycling in the bicycle lane (Mean = 2.41, SD = 1.25), a designated lane alongside the roadside shared by moderate traffic and controlled accesses. Some participants stated that they felt less concerned about cars approaching them directly in the bicycle lane due to the presence of traffic lights and the dedicated lane. They were also not anxious about the possibility of doors opening from parked cars. In contrast, regarding the bicycle path, participants rated this scenario higher than the bicycle lane because they were worried about the presence of pedestrians (Mean = 2.67, SD = 1.13). They mentioned that they were uncertain about how pedestrians would behave while passing, and they were afraid of potentially colliding with pedestrians. Furthermore, they highlighted that if the volume of pedestrians was higher, they might perceive a higher level of risk.

Table 5. Descriptive statistics of perceived level of risk in simulated scenarios.

Question	Descriptive Statistics	Scenario 1	Scenario 2	Scenario 3
Please rate the risk level	Mean (SD)	Shared-use road	Bicycle lane	Bicycle path with pedestrians
	Mean	3.77	2.41	2.67
	SD	1.07	1.25	1.13

In addition, participants were asked to rank the scenarios from least risky to riskiest, as shown in Figure 4. The results indicate that 49% of participants ranked Scenario 2, Scenario 3, and Scenario 1 from least risky to riskiest, while 23% of participants chose Scenario 3, Scenario 2, and Scenario 1 from least risky to riskiest. This indicates that more than 70% of participants ranked Scenario 1 as the riskiest. This confirms the results obtained from the descriptive statistics, which shows that Scenario 1, including shared-use road, is perceived as having a higher risk than other scenarios, including the bicycle lane and bicycle path.

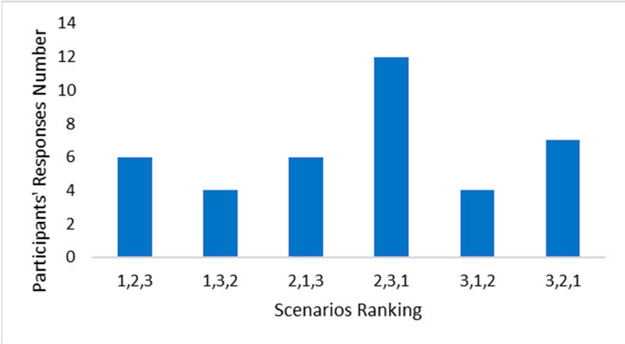


Figure 4. Participants' rankings of scenarios from least risky to riskiest.

3.3.2. Perceived Level of Risk Between Facility Types

Analysis of variance (ANOVA) tests are conducted to analyze the effects of different types of cycling facilities on the perceived level of risk. Participants were asked to evaluate the effect of the facility type with its specific road conditions on their level of risk. The ANOVA test is one of the most applicable methods in transportation data analysis [26]. ANOVA is a statistical test used to analyze the difference between the means of more than two groups. In this study, the dependent variable is the perceived level of risk, and the independent variable, which is the facility type, has three different categories: shared-use road, bicycle lane, and bicycle path. This method is used to evaluate whether the bicycle facility type has a significant impact on the perceived level of risk at the level of 0.05. Therefore, the study observes the significance of the association between facility type and the level of risk. The hypothesis is assumed as follows:

- Null hypothesis (H_0): There is no difference in the perceived levels of risk among the different types of bicycle facilities.
- Alternative Hypothesis (H_1): There is at least one type of facility with a different mean perceived level of risk.

The ANOVA test is conducted using R software. The results of this test are presented in Table 6. The significant *p*-value (0.0035) indicates that there is a statistically significant difference between at least two of the facility types. The calculated F-statistic (14.04) is greater than the critical F-value (3.08). The low *p*-value (<0.05) and significant F-statistic support the rejection of the null hypothesis, suggesting that there are significant differences in means among the different types of facilities. The ANOVA results indicate that there is significant variability in perceived levels of risk among the three facilities.

Table 6. Results of ANOVA Test.

Source of Variation	df	F-Ratio (F)	*p*-Value	Critical F-Value
Between Groups	2	14.04	0.00035	3.08
Within Groups	114			
Total	116			

The ANOVA results indicate differences among the categories of the independent variable but do not specify which differences are significant. A post hoc test, TukeyHSD (Tukey's Honestly Significant Difference), for pairwise comparisons is therefore considered to identify which specific facility type has a greater impact on the perceived level of risk.

The critical difference (CD) of 0.76 is vital for evaluating the significance of mean differences in a post hoc test. This value can be obtained based on a table that contains critical values $Q_{\alpha,k,v}$ for the Studentized Range distribution defined by $P(Q \geq Q_{\alpha,k,v}) = \alpha,\ k$, which is the number of degrees of freedom in the numerator (the number of treatment groups), and v is the number of degrees of freedom in the denominator (s^2) [32]. Tukey's post hoc test revealed significant pairwise differences between the shared road and bicycle lane scenarios, showing an absolute mean difference of 1.3 ($p < 0.05$) and between the shared road and bicycle path scenarios, with an average difference of 1.05 ($p < 0.05$). These differences are bigger than the critical difference, indicating a statistically significant difference between the shared road and bicycle lane scenarios and the shared road and bicycle path scenarios. However, the absolute mean difference between the bicycle lane and bicycle path scenarios is 0.25, which is less than the CD, indicating no statistically significant difference between these scenarios. Therefore, it can be concluded that the shared-use road scenario is perceived as having a significantly higher risk than the bicycle lane and path scenario, as supported by the observed absolute mean difference in the perceived risk. Participants felt that the shared-use road scenario was the riskiest.

3.3.3. Participants' Perceived Risk Comparison to Calculated Risk Index

Participants' overall perceived level of risk is compared to the calculated RI obtained from the previous research study [7] to study if the objective risk assessment can reflect the subjective risk perceptions of cyclists. As mentioned previously, the risk index includes nineteen factors, categorized into facility features, infrastructure characteristics, cyclists' behavior and demographics, and weather/traffic conditions. Therefore, all the risk factors included in the risk index are obtained for each virtual scenario with their level of occurrence. Furthermore, the average demographics of the participants are as follows: male, aged 26–49 years, and with average cycling level of experience. Their behavior was observed through the videos recorded, and it can be identified that they have high traffic violations and were moderately inattentive while driving. The weather conditions and the road surface conditions cannot be considered in the simulations as risk factors. Then, the risk index is calculated for each road segment using Equation (1):

$$RI = \sum_{i}(w_i \times V_i) \tag{1}$$

where RI = overall risk index of a road segment; w_i = weight of a risk factor in a single category; V_i = value of a risk factor that occurred within a road segment; and i stands for the number of the risk factors observed within the road segment [7].

This risk index quantifies the overall risk level for each road segment, considering the identified risk factors and their weights associated with each condition. The participants' perceived levels of risk are normalized to a range between 0 and 1 to align with the risk index. Figure 5 shows the comparison between the calculated risk index and the perceived risk. The percentage similarity between the two factors is obtained at 97.87%, indicating a significant alignment. Participants perceived a lower risk level compared to the one obtained by the risk index for Scenario 2 only.

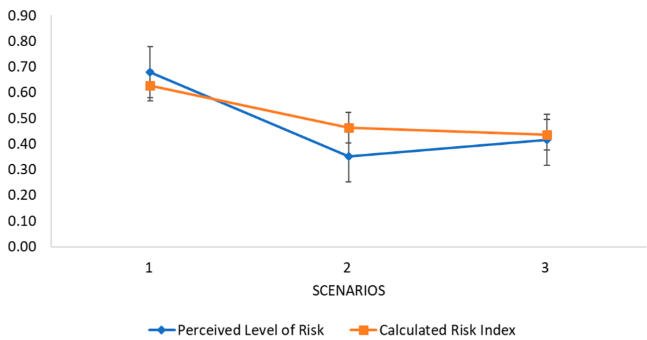


Figure 5. Comparison of calculated risk index and perceived risk.

3.4. Factors Impacting on Perceived Level of Risk

3.4.1. Traffic Conditions Impact

In this study, participants were asked to evaluate their perceived level of risk in Scenario 1 in current medium traffic conditions and then estimate their perceived level of risk if traffic conditions were higher. The purpose of this comparison was to study the isolated impact of traffic conditions on risk perceptions when cycling. Participants were given instructions to focus on evaluating perceived risk in relation to traffic conditions. They were encouraged to consider traffic-related risks while potentially disregarding other factors.

In this case, a t-test is used to evaluate the impact of two different traffic conditions on the perceived level of risk. The t-test serves as a statistical tool designed for comparing the perceived rating means of two groups: medium traffic and higher traffic conditions. This test aims to determine whether the differences observed in perceived risk levels between the traffic conditions are statistically significant [28]. This test was selected instead of the ANOVA test, as this method is more appropriate for comparisons involving multiple groups [28]. A t-test is calculated using Equation (2):

$$t = \frac{\overline{x}_1 - \overline{x}_2}{\sqrt{\left(s^2\left(\frac{1}{n_1} + \frac{1}{n_2}\right)\right)}} \tag{2}$$

where

- t is the t value.
- $\overline{x}_1$ and $\overline{x}_2$ are the means of the two groups being compared.
- s^2 is the pooled standard error of the two groups.
- n_1 and n_1 are the number of observations in each of the groups.

R software was used to compute the t-test. Based on the results, it can be identified that there is a statistically significant difference between the means of the high traffic and medium traffic conditions, with a p-value lower than 0.05. The perceived risk level of cyclists differs significantly between high and medium traffic conditions, with a higher perceived risk in higher traffic conditions.

3.4.2. Infrastructure Impact

The specific factors previously identified in the risk index are studied in this research. In reference to previous studies and risk assessments, the factors that are constantly present in simulated scenarios are considered, specifically the lane width, presence of obstacles, absence of safety barriers, and existence of accesses. Participants were asked to rate the influence of lane width, safety barriers absence, accesses presence, and obstacles presence on their perceived level of risk for the whole road layout. Each participant provided ratings for each risk factor separately to express their perceptions of the relative impact of safety barriers, accesses, and obstacles on perceived risk. Participants were presented with written descriptions of each risk factor, and oral explanations were given when requested. Accesses were defined as the existence of different complex intersections, different crossings, and different accesses to parking or buildings. Obstacles were considered as poles, bins, parked cars, trees, and other physical objects that may obstruct the path.

These factors are chosen due to their significant influence on perceived risk within different environments [7]:

- Lane width: This factor refers to the width of the track on which cyclists ride. The narrower the width, the greater the risk to cyclists compared with an adequate width.
- Obstacles existence: This factor refers to the presence of physical obstructions on the roads, such as bins, benches, parked cars/scooters, construction materials, or objects obstructing pathways. The existence of obstacles can increase the perceived level of risk and put the cyclists in danger, leading to single-bicycle accidents.
- Safety barriers absence: Safety barriers are protective barriers designed to provide protection or delineate boundaries along the road. The absence of safety barriers can increase the risk of accidents for cyclists.
- Accesses existence: Accesses mean the presence of entry points to a particular area, which can affect the flow of traffic and bicycle movement. They can include driveways,

entrances to facilities, etc. The existence of accesses can introduce complexity to the environment and increase collision risks between cyclists and other road users.

The data were collected using a five-point rating scale ranging from very high to very low. This methodology allowed for the evaluation of each factor's impact on perceived risk levels. The Friedman test, a non-parametric statistical test designed for comparing multiple related groups in which the same number of participants in each group [31], was used to analyze the collected data and evaluate any potential differences among the four risk factors. The hypotheses tested are as follows:

- Null Hypothesis (H_0): The mean impact of factors is all equal.
- Alternative Hypothesis (H_1): At least one mean factor is different from the rest.

R software was used to conduct the Friedman test. Analyzing the results of the Friedman test showed that the associated *p*-value is small (<0.05), which indicated that, in this case, the H_0 hypothesis should be rejected. Therefore, there was strong evidence showing that there were statistically significant differences among the factors based on the ratings provided by participants.

Since the null hypothesis was rejected, the Wilcoxon test was conducted to calculate the *p*-values for each pair of columns. This test was applied to pairwise comparisons of the factor levels to identify where differences lie [31]. The results of the post-comparison test are shown in Table 7. It presents the *p*-values from pairwise comparisons between the different factors. Each cell in Table 7 presents the *p*-value for comparing the row level with the column level. The hyphen indicates that no comparison is applicable for those cells, as factors cannot be compared to themselves. The "Accesses Presence" and "Safety Barriers Absence" factors differed significantly from the "Width" factor ($p < 0.05$). This indicated that the means were significantly different among these factors only.

Table 7. Pairwise Wilcoxon test results for factor comparison.

	Width	**Safety Barriers Absence**	**Accesses Presence**
Safety Barriers Absence	0.0004	-	-
Accesses Presence	0.0015	1	-
Obstacles Presence	0.2151	0.5462	1

It can be concluded that the absence of safety barriers and the presence of accesses have almost the same impact on the perceived level of risk. Moreover, safety barrier absence is the factor with the highest impact on the perceived level of risk.

3.4.3. Perceived Additional Risk Factors Identified by Participants

Participants were asked about additional factors in the scenarios that they thought posed dangers. Most participants said they did not consider any additional factors as risky (61%). On the other hand, of those who did mention additional factors, 26% of participants identified the existence of curvature as a risky factor. This comment highlights the perceived danger associated with curves in the road layout, as they may reduce visibility and raise the possibility of bicycle accidents. Furthermore, 6% of participants mentioned the presence of some parked cars as a risk factor, which can be aligned with the concept of the presence of obstacles.

3.4.4. Gender Effect on Perceived Level of Risk

When considering the gender effect, Figure 6 shows a significant difference in the perceived level of risk between genders across different scenarios. Female participants have a significantly higher level of perceived risk than male participants for two scenarios: Scenario 2, which involves a bicycle lane together with vehicles, and Scenario 3, which involves a bicycle path shared with pedestrians. It can be concluded that female participants generally perceive higher levels of risk than males. Furthermore, male participants show a higher difference in the perceived level of risk among the three scenarios. They rate riding in Scenario 1 (which involves a shared road) as high risk, while they rate the other scenarios as low risk. Overall, the results highlight that females reported higher perceived risks across scenarios.

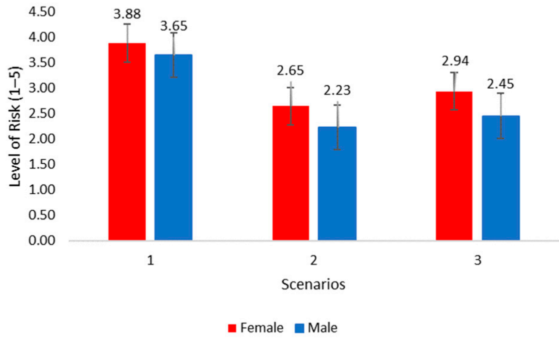


Figure 6. Perceived level of risk of different gender groups.

3.4.5. Age Effect on Perceived Level of Risk

The age of the participants was divided into three groups: 18–25 years, 26–49 years, and 50–59 years. Participants aged 18–25 report the highest perceived risk (M = 4.33) in Scenario 1, as shown in Figure 7. The 18–25 age group also has the highest perceived risk (Mean = 2.73) in Scenario 2. Participants aged 26–49 report the lowest perceived risk in this scenario (M = 2.10). In Scenario 3, participants aged 18–25 report the second-highest perceived risk (M = 2.97). The results highlight that the younger age group reported higher perceived risks across scenarios.

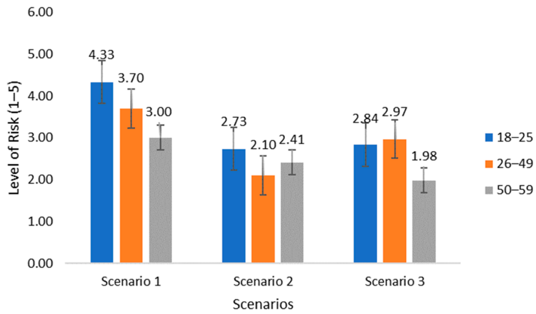


Figure 7. Perceived level of risk of different age groups.

3.4.6. Bicycle Level of Experience Effect on Perceived Level of Risk

Two groups were identified based on the bicycle experience level of the participants: experienced and inexperienced. Figure 8 shows the analysis of the perceived risks for each of the three scenarios, Scenarios 1, 2, and 3. Less experienced participants (M = 4.29; M = 2.80; M = 3.13) report the highest perceived risk. Experienced participants generally perceive lower risks in all three scenarios, according to the data. This indicates a comfort level with cycling facilities.

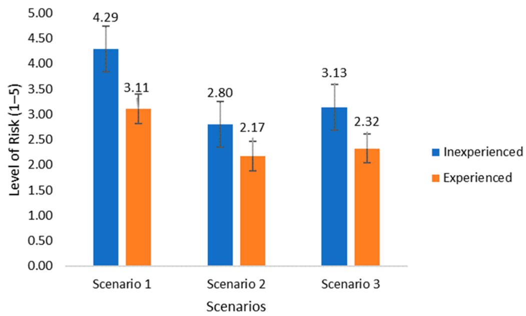


Figure 8. Perceived level of risk of different bicycle levels of experience.

4. Discussion

Thirty-nine participants provided a quantitative assessment of the perceived level of risk across different cycling environments simulated on the bicycle simulator. This section provides a discussion of the results from the pre-survey and post-survey questionnaire analyses and highlights the limitations of the study.

Based on the pre-survey questionnaire, men were more involved in bicycle accidents than women. This indicates a higher proportion of men involved in such accidents, as shown in previous research studies [33]. The main risk factor behind previous accidents among the participants is infrastructure, as indicated by a previous study, which considers this factor to be one of the riskiest, putting cyclists at risk [7]. Furthermore, a significant problem can be identified regarding the reporting of bicycle accidents. Despite experiencing previous bicycle accidents, a majority of participants did not report them to the police. This indicates that bicycle accidents are underreported, which aligns with previous research studies. The limited involvement of cyclists in official police reports has highlighted a potential gap in considering the extent of bicycle-related accidents in research and official records [34,35]. This limitation prevented us from relying completely on accident police records for bicycle safety analysis. It is important to integrate other methods, such as bicycle simulators and real-road observations, as alternative approaches to address this challenge and conduct an in-depth analysis of bicycle accidents. Therefore, a bicycle simulator was used in this study to provide a controlled, safe environment by replicating a real road in Stockholm to examine the perceived level of risk and cyclist behavior.

The purpose of the post-survey was to study the correlation between the perceived risk levels in the different scenarios and the calculated risk index. The results indicate a close correlation between the perceived risk levels and the risk index in most scenarios, with the exception of Scenario 2, which shows a minor difference. In this scenario, participants reported a perceived risk lower than the risk index, emphasizing that they felt safer and more aware due to the presence of a cyclist in front of them. Most participants did not overtake the cyclist, so the perceived risk was lower due to reduced speed and increased attention. On the other hand, participants expressed uncertainty regarding pedestrian behavior in the final scenario, raising the possibility of accidents when passing them. Furthermore, participants perceived Scenario 1 as having the highest risk, which is aligned with the calculated risk index. This strong alignment confirms that the risk index matches the participants' perceived risk levels. The risk index that was obtained from the earlier research can be considered to be a reliable tool for evaluating risk. This risk index can be used by any policy-maker and urban planner to measure the degree of risk of roads and identify gaps in the cycling roads for better decisions and infrastructure improvement to enhance the cyclists' safety. The proposed risk index can also be added to any map and used to develop a real-time alert system for cyclists that warns them of the risks associated with certain areas of the road segment based on their current speed.

According to participants' responses, the three risk factors, such as the presence of accesses, the presence of obstacles, and the absence of safety barriers, appear to have an almost equal impact on the level of perceived risk, with the absence of safety barriers having a greater effect than the others. These results differ from previous research studies, which highlight the significant risk posed by road accesses such as intersections and driveways [36], obstacles encountered by cyclists. Studies have shown that these factors contribute significantly to accidents and injuries among cyclists. For example, previous research conducted by [37] indicates that a roadway segment with a higher density of driveways experiences a significantly higher rate of accidents compared to segments with fewer driveways. Regarding obstacles, studies have reported a reasonable percentage of cyclists colliding with obstacles, leading to injuries. For example, 31% [38] and 20% [33] of cyclists collided with different obstacles, causing injuries. In contrast, research on the absence of safety barriers is limited. While some studies suggest that safety barriers can reduce the severity of accidents and run-off-road accidents [37], there is a lack of accident data analysis to measure the frequency and severity of accidents related to this risk factor.

The disagreement between perceived ratings of risk factors and existing research suggests that the virtual environment may influence participants' perceptions in ways that differ from real-world situations concerning specified risk factors. Some risk factors cannot be fully analyzed in the simulator environment. Therefore, to gain a deeper understanding of how the risk factors contribute to perceived and actual risk, the next step in our future studies will involve real road experiments. The bicycle will be equipped with different sensors such as GPS, a speed sensor, a triaxial accelerometer, a distance sensor, and an eye tracker. When participants ride on a real road, they will be exposed to the typical risk factors that cyclists encounter during everyday riding. These future experiments aim to evaluate the relative importance of each risk factor in contributing to bicycle accidents. The transition from simulated to real road experiments will enable a deeper understanding of how both perceived and actual risks interact, correlating eye tracker data with the sensor data to identify specific locations where risk perception and risk factors align.

Concerning the impact of demographics on the perceived level of risk, the analysis of demographic data, considering factors such as age, cycling level of experience, and gender, emphasizes their impact on the perceptions of risk during different cycling scenarios. The results show that women perceive risks in all scenarios to a greater extent than men. This suggests that they may be more cautious than men, consistent with previous research findings [20,39]. The variation in risk perception based on gender highlights how it is important to consider different viewpoints when evaluating the risks associated with various cycling situations and creating bicycle-friendly spaces that take safety precautions into account. The study also showed that younger participants (18–25 years old) reported higher perceived risks across different scenarios, indicating a sensitive sense of caution while cycling. Furthermore, inexperienced participants reported higher perceived risks, which emphasizes the impact of the level of cycling experience on risk perception. This study contributes to validating the influence of demographics on the risk perceptions of road segments and paving the way for the importance of developing proactive safety initiatives to promote a safe environment for cyclists of different demographics.

5. Conclusions

This study presents the results of studying the perceived level of risk and risk factors using a bicycle simulator by means of a survey questionnaire. The simulator showed reliability in evaluating cyclists' perceptions of roads by providing close-to-reality displays of different scenarios with minimal oculomotor symptoms linked to simulator sickness.

Participants felt that the first scenario—which included the shared road—was significantly riskier than the other scenarios, which had bicycle lanes and paths. These findings aligned with the calculated risk index. Therefore, the risk index can be considered a reliable formula for risk evaluation and can be used by policy-makers and other stakeholders to evaluate road segments. This research focused on cyclists' perspectives in measuring the perceived level of risk, particularly concerns about potential collisions and the unpredictability of pedestrian movements. Therefore, to address the limitations of this study, two future studies will be conducted. One of the future studies will be focused on the development of virtual reality (VR) scenarios using a VR headset and the inclusion of virtual cyclists in order to study other road users' viewpoints. This approach will allow us to understand pedestrian perceptions and behaviors concerning interactions with cyclists at different points and compare these perceptions to those of cyclists.

Our findings highlight that higher traffic volume, the absence of safety barriers, and the existence of access points can increase the perceived risk levels for any road segment type. Finally, the bicycle simulator appears to be a promising method of evaluating cycling facilities, which offers valuable data for researchers, urban planners, and policy-makers. For this reason, the second follow-up study will conduct real experiments on the road, building an instrumented bicycle and asking participants to ride on a road layout with different conditions to study additional risk factors and identify their levels of importance.

While the sample in this study has respectable gender representation, it is important to consider several limitations of this study. A larger sample including a diverse range of demographic characteristics is essential to examine their effects on perceived levels of risk using statistical analysis methods for a more detailed analysis. Therefore, future research will aim to recruit participants from diverse demographic backgrounds to improve the reliability of findings.

Author Contributions: Conceptualization, L.A., H.I., F.D.C. and C.L.; methodology, L.A., H.I., F.D.C. and C.L.; software, H.I.; validation, L.A., H.I., F.D.C. and C.L.; formal analysis, L.A.; investigation, L.A. and H.I.; resources, L.A. and H.I.; data curation, L.A. and H.I.; writing—original draft preparation, L.A.; writing—review and editing, L.A., C.L., F.D.C. and H.I.; visualization, L.A.; supervision, C.L., F.D.C. and H.I.; project administration, C.L., F.D.C. and H.I.; funding acquisition, H.I. All authors have read and agreed to the published version of the manuscript.

Funding: This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie COFUND grant agreement No. 101034248.

Funded by
the European Union

Institutional Review Board Statement: This research was conducted in accordance with the principles outlined in the Declaration of Helsinki. As a non-interventional study, it did not require ethical review or approval under French law.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data supporting the study are not publicly available due to privacy restrictions. The sharing of data is restricted to ensure the confidentiality and privacy of participants under ethical guidelines and institutional policies. However, additional details may be available from the corresponding author (L.A.; lama.ayad@univ-eiffel.fr) upon request.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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