

Studying the Interaction between Vulnerable Road Users and Automated Vehicle

A Pedestrian-Cyclist Virtual Reality Co-simulator
and Experiment in Shared Space

TIL Master's Thesis
Zhenlin Xu

Studying the Interaction between Vulnerable Road Users and Automated Vehicle

A Pedestrian-Cyclist Virtual Reality
Co-simulator and Experiment in Shared Space

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Zhenlin Xu

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Thesis committee: Dr. Eleonora Papadimitriou, TU Delft, supervisor
Dr. Yan Feng, TU Delft, supervisor
Prof. dr. ir. Serge Hoogendoorn, TU Delft, additional examiner

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Preface

I would like to dedicate this thesis to my grandfather.

I'm grateful for the opportunity to present my research *Studying the interaction between vulnerable road users and automated vehicle: A pedestrian-cyclist virtual reality co-simulator and experiment in shared space*, as the conclusion of my master program in Transport, Infrastructure, and Logistics at Delft University of Technology.

I'm deeply thankful to Dr. Yan Feng for introducing me to virtual reality and for the opportunity to be her supervised student. The experience of working as her research assistant in the Mobility in eXtended Reality Lab has been invaluable. I also want to express my appreciation to my friends Yixin Sun, Yiman Bao, and Danya Li for their support with the co-simulator development and the preparation of the VR experiments.

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Finally, I am profoundly grateful to my parents for their unwavering support throughout my journey at TU Delft. I sincerely hope they are proud of this thesis.

I hope you find this work both enjoyable and insightful!

Zhenlin Xu
Delft, January 2025

Summary

Introduction

Vulnerable Road Users (VRUs), such as pedestrians and cyclists, face higher traffic risks due to their lack of external protection. Studying their behaviors is crucial for improving road safety and reducing injuries. The introduction of Automated Vehicles (AVs) presents potential risks for VRUs, as these vehicles differ from human-driven ones. VRUs often rely on implicit communication, like eye contact and gestures, to navigate interactions with human drivers. Hence, examining VRU-AV interactions is essential to ensure safety and acceptance.

Traditional methods of studying VRU behavior, including field observations, surveys, and video recordings, are insufficient for exploring VRU-AV interactions due to the limited deployment of AVs. Recently, Virtual Reality (VR) experiments have emerged as a new method, offering a safe and efficient way to study VRU behavior. VR can simulate realistic and hypothetical scenarios, making it particularly effective for studying interactions between VRUs and AVs.

Despite the growing interest in VR experiments, there are several research gaps. Most current VR studies focus on isolated, single-participant scenarios, failing to capture group dynamics and multi-modal interactions. There is a need for more research on how group behaviors influence VRU-AV interactions and the interactions between different groups of road users. Additionally, existing VR studies often use simplified representations of pedestrians, which may not capture the full complexity of human interactions. Therefore, developing a more realistic VR co-simulator with multi-player functionalities is essential for enhancing simulation fidelity and realism.

Therefore, this master's thesis addresses the research question: *“How can a multi-player multi-modal road user virtual reality co-simulator be developed and tested to study the behaviors and interactions between various vulnerable road users?”*

Simulator Design

To begin with, the simulator integrates existing pedestrian and cyclist VR simulators to create a cohesive multi-player environment. Using Unreal Engine 5, the platform supports multi-player functionality, allowing users to engage within the same virtual space. A server-client architecture is implemented, choosing the listen server for its simplicity and suitability for VR experiments with a small number of participants. Detailed synchronization of player actions is achieved through replication, encompassing complex data such as body movements and eye-tracking.

In terms of interaction development, body tracking plays a vital role in capturing the realistic movements of road users. The pedestrian full-body tracking system includes the head, spine, hands, and feet, while cyclist tracking focuses on the upper body to simulate gripping the handlebars. Additionally, MetaHuman is employed to create lifelike human representations, enhancing the immersive experience for users.

For data collection, the co-simulator meticulously records trajectory data, capturing the positions and movements of participants within the virtual environment. Furthermore, behavioral data, including implicit communications like eye contact and gestures, are gathered to provide insights into the decision-making processes of road users. The body-tracking system records comprehensive movement data, ensuring a precise representation of behaviors for in-depth analysis.

Methodology

In this study, immersive VR experiments were utilized to showcase the capabilities of a multi-player, multi-modal VR co-simulator designed to investigate the behaviors and interactions of various road users. Specifically, the VR experiments focused on interactions between VRUs, such as pedestrians and cyclists, and autonomous vehicles AVs in shared spaces.

The VR experiment aimed to assess both the design and development of the co-simulator and the impact of

VRU role, number, and initial location on their behaviors and interactions with AVs. A within-subject design was employed to mitigate individual differences. Three within-subject variables were considered: the number of VRUs (1 or 2), the role of VRUs (pedestrian or cyclist), and their initial location relative to the AV (far or close). The experiment included 10 road-crossing scenarios organized into four blocks: single pedestrian crossing, single cyclist crossing, dual pedestrian crossing, and pedestrian-cyclist joint crossing. In each scenario, the AV consistently yielded to participants without explicitly communicating this behavior.

The VR experiment involved 40 participants (20 pairs), all of whom had normal or corrected vision and normal mobility. Data collected during the experiments included both objective and subjective measures. Objective data encompassed movement trajectories, eye gaze, and body tracking, recorded continuously and stored in CSV files. Subjective data were gathered through a post-experiment questionnaire covering participant information, system usability, simulator sickness, realism, presence, trust in AVs, perceived behavior control and risk, and feedback. Metrics for analysis included negotiation time, crossing time, space gap, total distance, average speed, and AV-gazing time. A linear mixed model analysis was used to evaluate these metrics.

Results and Discussion

Co-simulator Assessment

To assess the effectiveness of the developed VR co-simulator, a VR experiment was designed and conducted. Participants filled out a post-experiment questionnaire that assessed simulator sickness, realism, presence, and body-tracking usability. The findings indicated that the overall experiment did not induce excessive motion sickness, similar to previous studies. However, feedback suggested that the bike VR simulator could benefit from improvements in steering and acceleration/brake control. The study achieved higher scores for presence and realism compared to previous research, thanks to the inclusion of high-quality, full-body representations and real-time tracking of road users. The system usability for body-tracking was deemed adequate, indicating user acceptance, although further enhancements to the body-tracking algorithms are needed to improve accuracy and flexibility. Overall, the VR experiment was successful, validating the effectiveness of the VR co-simulator and highlighting its potential contributions to transportation research.

VRU-AV Interaction

The VR experiment also investigated the effects of the number of VRUs, their role, and their initial relative location on the VRUs' behaviors and interactions with the AV in shared space. Both objective metrics and subjective measures were analyzed.

The results showed that the number and role of VRUs significantly influenced pedestrians' negotiation time, total walking distance, AV-gazing time, and the space gap for both pedestrians and cyclists. Pedestrians' movement dynamics were affected by the presence of neighboring pedestrians when crossing as part of a group, consistent with previous studies. This behavior extended to mixed groups of pedestrians and cyclists. Cyclists' behaviors, however, remained largely unchanged, except for slight adjustments in space gaps, suggesting that cyclists perceive the presence of other VRUs differently.

The relative location of the VRUs significantly impacted pedestrians' negotiation time and space gap, with interaction effects between relative location and VRU combination being significant. More cooperative crossing behaviors were observed among VRUs, differing from previous findings that relative positions could lead to varying behaviors among pedestrians.

Subjective measures also provided insights into the effect of VRUs' count and role. Participants reported higher trust in AVs and greater confidence when crossing the shared space with another VRU, aligning with the objective metrics.

Overall, the study confirmed the influence of the number of VRUs, their role, and initial relative location on VRU-AV interaction in shared space. The decreased negotiation time and AV-gazing time, when pedestrians crossed together, highlighted the role of mutual awareness and implicit coordination in crossing decisions. These findings underscore the importance of considering both individual and collective dynamics in shared space studies, as synchronized behaviors and reduced attention to AVs may indicate increased confidence and trust among group members when navigating complex traffic scenarios.

Conclusion

In summary, we have successfully created and implemented a multi-player, multi-modal VR co-simulator that integrates both pedestrians and cyclists into the same VR environment. This VR co-simulator is designed to facilitate multi-player, multi-modal VR experiments, enabling comprehensive data collection for transportation research. It includes advanced features like body tracking for pedestrians and cyclists, the use of MetaHuman for high-quality digital human representation, as well as extensive data collection technologies such as body tracking and eye gazing data. A subsequent VR experiment was conducted to test the effectiveness of the developed VR co-simulator and to investigate the interaction between VRUs and AVs in a shared space. The evaluation of the co-simulator confirmed its capabilities and feasibility in terms of simulator sickness, presence, realism, and usability. Additionally, the VR experiment demonstrated the impact of different VRU combinations and their initial relative positions on the interaction between VRUs and AVs in shared space.

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Nomenclature

Abbreviations

Abbreviation	Definition
VR	Virtual Reality
VRU	Vulnerable Road User
AV	Automated Vehicle
HDV	Human-Driven Vehicle
eHMI	External Human-Machine Interface
LMM	Linear Mixed Model
SUS	System Usability Scale Questionnaire
SSQ	Simulator Sickness Questionnaire
PQ	Presence Questionnaire
PBC	Perceived Behavioral Control
PR	Perceived Risk
XR	eXtended Reality
MR	Mixed Reality
AR	Augmented Reality

Symbols

Symbol	Definition	Unit
$T_{negotiation}$	Negotiation time	[s]
$T_{crossing}$	Cross time	[s]
D_{gap}	Space gap	[m]
V_{total}	Crossing speed	[m/s]
D_{total}^{ped}	Pedestrian walking distance	[m]
T_{AV}^{ped}	Pedestrian AV-gazing time	[s]

Introduction

1.1. Research Backgrounds

Vulnerable Road Users (VRUs) refer to individuals on the road who lack the protection of an external shield, such as pedestrians and cyclists [1]. Due to their limited protection, VRUs usually face higher traffic risks than other road users [2]. Studying the VRUs' behaviors is necessary for enhancing road safety and reducing VRUs' injuries.

With recent advancements, Automated Vehicles (AVs) become promising to be deployed shortly. Compared to human-driven vehicles (HDVs), AVs will represent a new type of road user. This shift may pose potential risks for VRUs [3], who rely on not only explicit but also implicit communication, such as eye contact and gestures [4], with human drivers to negotiate. Therefore, investigating these potential VRU-AV interactions is essential to assess the safety, comfort, and acceptance of AVs by VRUs.

Traditionally, the road behaviors of VRUs are collected through various methods such as field observation [5, 6], surveys [7, 8, 9], and video recording [10, 11]. Field observations and video recordings provide objective data on the natural behaviors and interactions of VRUs with vehicles, while surveys offer a straightforward means to assess road users' subjective experiences. However, since AVs are not yet officially deployed worldwide, these conventional data collection methods are inadequate for effectively studying VRU-AV interactions.

In recent years, Virtual Reality (VR) experiments have become a new data collection method, providing a safe and efficient way to study the VRUs' behaviors [12]. By creating immersive and interactive environments, VR experiments allow participants to engage with traffic scenarios as if they were in real-world conditions. Additionally, VR experiments can simulate hypothetical or futuristic scenarios, avoiding the potential safety and ethical issues associated with field experiments. These features make VR experiments particularly effective for studying interactions between VRUs and AVs [13, 14].

1.2. Research Motivations

As interest in VR experiments to study VRU behaviors and interactions with AVs grows, several research gaps remain to be addressed.

A majority of the current VR studies on VRU-AV interactions concentrate on isolated, single-participant scenarios, typically focusing on a single pedestrian [13, 15] or a single cyclist interacting with vehicles [14] (either AVs or HDVs). While these studies provide valuable insights into individual behaviors, they fail to capture the collective behaviors within the VRU groups [16]. In real-world road situations, VRUs do not always cross the street alone. Only several studies [17, 18, 19, 20] involving two pedestrians crossing the road together, as shown in Figure 1.1. Therefore, more efforts are needed to **investigate how group dynamics influence VRU-AV interactions**.

Furthermore, most existing VR studies do not account for multi-modal interactions. Multiple groups of road users [21] introduce a higher complexity level compared to single-modal traffic scenarios [13, 14]. Overlooking these multi-modal interactions fails to represent realistic road behaviors accurately. Only a few studies focus on pedestrian-driver interactions [22, 23], as shown in Figure 1.1. Hence, it is also essential to put in more effort to

study the interactions between different groups of road users.

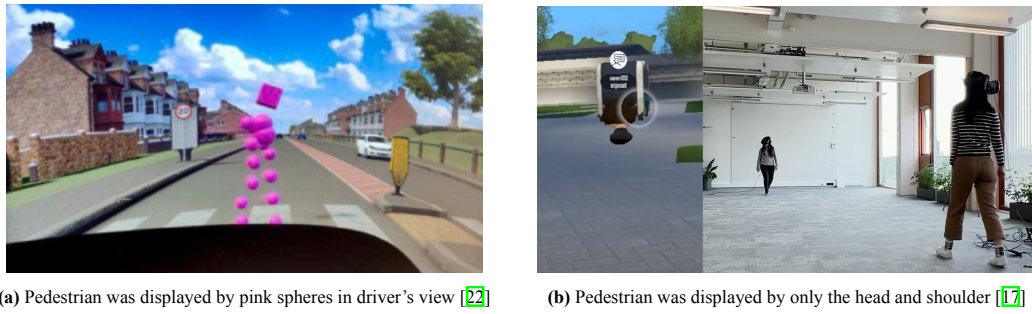


Figure 1.1: The body representations in VR in the previous study.

Additionally, in the limited literature involving multi-player and multi-modal interactions [17, 22, 23], the simulated interactions in VR remain too over-simplified and incomplete. For example, pedestrians are often represented with only partial body representations [17] or merely with several geometric proxies [22, 23], as shown in Fig 1.1. These representations may not be sufficient to capture human interactions' full complexity and realism, potentially introducing bias into the research findings. Thus, it's crucial to **develop a more realistic VR co-simulator to enhance simulation fidelity and maintain realism with multi-player functionalities.**

1.3. Research Objectives

Based on the research motivations, the objectives of this study are as follows:

1. *VR Co-simulator*: To design and develop a multi-player multi-modal VR co-simulator. This co-simulator aims to address the need for more realistic and versatile VR simulator studies, serving as a valuable research instrument for the road traffic research community.
2. *VRU-AV Interaction Study*: To investigate the VRUs' behaviors and their interactions, for instance, pedestrians and cyclists interacting with the AV within the context of the shared space road environment.

1.4. Research Question

1.4.1. Main Research Question

VR experiments are gaining popularity as a method for data collection in transportation research [12]. However, a significant gap persists in current research: most studies focus on individual road user behavior under various traffic conditions [13, 14], while the interactions between different road users within VR experiments remain largely unexplored [17, 22]. The development of multi-player, multi-modal VR experiments is still limited, mainly due to the lack of advanced multi-player VR co-simulators.

Considering the research objectives outlined, the main research question of this study can be formulated as follows:

How can a multi-player multi-modal road user virtual reality co-simulator be developed and tested to study the behaviors and interactions between various vulnerable road users?

1.4.2. Research Sub-questions

Five sub-research questions are formulated to further address the main research question.

Research Sub-question 1: Simulator Integration

The current research reveals a significant gap in the integration of various existing VR simulators, particularly those for pedestrians and cyclists, into a unified multi-player, multi-modal co-simulator. While individual simulators exist for different transportation modes, there is still a lack of effectively combining these disparate systems into a cohesive, interactive virtual environment. Therefore, the following sub-research question is formulated:

How can various existing VR simulators be effectively linked and integrated into a unified multi-player multi-modal co-simulator?

Research Sub-question 2: Interaction Development

A key challenge in implementing a multi-player multi-modal VR co-simulator is ensuring and facilitating realistic human interactions within the virtual environment, in contrast to the previous simple representation [17, 22]. Consequently, the following sub-research question is developed:

What types of interactions between different road users should be simulated in VR to achieve a similar level of realism as in the real world?

Research Sub-question 3: Data Collection

The introduction of multi-modal and multi-player capabilities opens up the possibility of collecting a wide array of new behavioral and interaction data sets. Investigating the types of comprehensive data that can be collected through this system holds great potential. Therefore, we have formulated the following sub-research question:

What kinds of data from different road users during a multi-player VR experiment can be collected?

Research Sub-question 4: Experiment Study

The ultimate goal of developing and utilizing this VR co-simulator is to facilitate the study of behaviors and interactions among VRU-AV interactions. To evaluate the functionality of the VR co-simulator and demonstrate its potential for transportation research, we pose the following research question:

How to design a multi-player multi-modal VR experiment to assess the effectiveness of the built simulator and investigate the interaction between different road users?

Research Sub-question 5: VRU-AV Interaction

Besides the assessment of the VR co-simulator, the proposed VR experiment will study the collective behaviors of VRUs and their interaction with the AV in shared space, hence the last sub-research question is formulated as follows:

How do the number of VRUs, their role, and their initial relative location influence the VRUs' behaviors and their interactions with the AV in shared space?

1.5. Research Contributions

This study offers several important contributions to the field:

- This study introduces a pioneering multi-player, multi-modal VR co-simulator that leverages advanced VR interaction features, such as full-body tracking, high-quality digital human representation MetaHuman, significantly advancing VR as a tool for multi-agent experiments.
- It investigates the interactions between pedestrians, cyclists, and AVs within a VR environment, offering a novel approach to analyzing the behaviors and interactions of various VRUs.
- It emphasizes attention on shared space, providing an in-depth analysis of the complex interactions between pedestrians, cyclists, and AVs.

1.6. Thesis Structure

The structure of the remainder is as follows: Section 2 begins with a comprehensive review of the relevant literature. Next, Section 3 introduces the multi-player multi-modal VR co-simulator. Section 4 describes a multi-player VR experiment as a case study. In Section 5, the findings from the data analysis are presented and discussed. Section 6 answers the research questions and Section 7 concludes the thesis.

2

Literature Review

This chapter presents a comprehensive literature review. Section 2.1 examines prior studies on the crossing behaviors of VRUs. Following this, Section 2.2 reviews various traditional data collection methods. Next, Section 2.3 introduces the VR experiments as a new data collection method for VRU-AV interaction. Then, Section 2.4 delves into recent research focusing on shared spaces, a trend in road design. Lastly, Section 2.5 summarizes the research gaps.

2.1. VRU Crossing Behaviors

Understanding the road crossing behaviors of VRUs, such as pedestrians and cyclists, [1] is vital for enhancing road traffic safety. This section reviews the crossing behaviors of two main groups of VRUs: pedestrians and cyclists.

2.1.1. Pedestrian Crossing Behaviors

Pedestrian crossing behavior is a central focus in VRU behavior research and road safety [1]. The complexity of pedestrian crossing behavior arises from the intricate decision-making process involved, which is influenced by a multitude of factors, including individual characteristics [24, 25], human factors [26, 27, 28], road and traffic conditions [24, 26], and social information use [16, 17, 29].

Individual characteristics are critical in shaping pedestrian crossing behavior. Several individual characteristics including age [24, 30], gender [24, 25], the experience of car accidents [24], and baggage condition [25], have been studied, and identified as factors influencing pedestrians' crossing behaviors and causing potential risky conflicts and dangerous situations. Furthermore, human factors [26] are also considered in pedestrian crossing behaviors, such as risk perception, risk proneness, travel motivation, and attitude towards walking. [27, 28] studied the effect of distraction like mobile phone use on pedestrian crossing behavior at high-risk intersections. In addition, external factors such as traffic flow [24], and infrastructure design [24, 26] also significantly impact pedestrian crossing behavior.

Crossing scenarios do not always involve a single pedestrian. Interactions with others, whether as part of a pair [17] or a group [16, 29], also play a significant role in shaping individual behavior patterns during group crossings. For example, [16] reported that neighbors of a crossing pedestrian tended to cross before other waiting pedestrians. It also discovered the cases in which individuals started to cross and then returned to the roadside, frequently found in groups. In [17, 29], the effect of other pedestrians as the social context was further explored.

With the rapid development of AVs, AVs are expected to be deployed soon, co-existing with HDVs. Hence, pedestrians' interactions with AVs have become a new research focus. Research interests include pedestrian perception of AV [31, 32, 33], road user behaviors with AV [17, 15, 18, 19, 23], and eHMI design [29, 34, 35, 36, 13]. A detailed literature review of pedestrian-AV interaction can be found in [37].

2.1.2. Cyclist Road Behaviors

Besides pedestrians, cyclists are also another important group of VRUs [1]. The cyclist's road behaviors include not only crossing behaviors, but also other risky operations (i.e., overtaking behaviors), and rule violations [38]. Overall, the road behaviors of cyclists are influenced by several categories of factors, including individual characteristics [8, 39, 40], infrastructure [41, 42], and group dynamics [43, 44]. Understanding these elements is crucial to designing safer and more cyclist-friendly urban infrastructure.

Individual characteristics, such as age [8, 39], gender [8, 39, 40], and experience level [39] significantly influence cyclist crossing decisions. [8] reported male and younger cyclists were found to commit more violations and less positive behaviors compared to female and older ones across three countries (Australia, China, and Colombia). The same conclusions were confirmed by [39], which focuses on a group of young cyclists aged from 15 to 24 in China. The result also revealed the contribution of risk perception and cycling skills to cyclist safety. Meanwhile, the design of road infrastructure and surrounding environmental conditions [41, 42] heavily influence cyclist road safety. More details could be referred from a recent literature review on cyclists' behavior research in [38].

Cyclists' crossing behavior is often shaped by interactions with other road users, including motorists, pedestrians, and cyclists. Cyclists riding in groups behave differently than those riding alone [38, 43]. [43] reported that teamwork factors may make behavioral interventions to decrease risky behaviors easier to implement with group cyclists compared to individual cyclists, thus leading to safer road behaviors.

2.2. Traditional Data Collection Methods to Study VRU-AV Interaction

As an empirical discipline, transportation research depends on data collection to analyze, model, and understand road user behaviors. Traditional methods for studying VRUs' behaviors include field observations, surveys, video recordings, etc [37]. This section examines these methods by considering previous research on the behaviors of road users and the interactions between VRUs and AVs.

2.2.1. Field Observation

Field observation [5, 6, 45] is a fundamental approach for capturing road user behaviors, such as their trajectories, in the natural environments. This method allows researchers to gather naturalistic data on how people interact with transportation systems. For instance, in [5], participants were asked to complete eight short walking trips to document their crossing behaviors under varying road and traffic conditions.

In VRU-AV interaction studies, Wizard of Oz experiments [6, 45] are commonly used to simulate the presence of AVs. With a concealed driver inside, the vehicle appears as an AV from the viewpoint of VRUs. The study [6] focused on evaluating pedestrians' decisions to cross the road when interacting with an AV versus a conventional vehicle. Meanwhile, [45] investigated how eHMI, acoustic signals, pitch motion, and their combinations impact pedestrians' crossing behavior and perceived safety.

2.2.2. Survey

Surveys [7, 8, 9] are among the most common methods for understanding participants' subjective views on the research topic. In [7], a pan-European survey was conducted to identify patterns in pedestrian attitudes, perceptions, and behaviors across Europe. A cyclist behavioral questionnaire was conducted across three different countries, namely Australia, China, and Colombia in [8]. Surveys can not only be utilized independently but also in combination with objective data collection methods [9]. For example, [9] conducted a comparative study of pedestrians' self-reported and observed crossing behaviors using both field observations and questionnaires.

For studying the VRU-AV interaction, surveys are usually used to assess the subjective perspective of VRUs. [33] examined how pedestrians and bicyclists perceived AV safety based on their understanding and experiences in Pittsburgh, US via a questionnaire called the 2019 BikePGH survey. Additionally, surveys are used alongside VR [13, 14, 17] or wizard of Oz [6, 45] experiments to gather participants' subjective feedback.

2.2.3. Video Recording

With advancements in camera technology and algorithm development [46], video recordings have emerged as a widely used method for automated data collection [10, 11]. For instance, [10] analyzed pedestrian and vehicle traffic at four pedestrian crossings in Poland to evaluate pedestrian safety, using dedicated video analysis

algorithms to extract interactions meeting specific criteria. Similarly, [11] introduced two top-view pedestrian trajectory datasets capturing vehicle-crowd interactions from controlled experiments and a campus environment. Additionally, drones have become a valuable tool for video recording in various studies [47, 48].

Due to the limited number of AVs currently operating on the roads, video observation studies on VRU-AV interactions are scarce. Consequently, stationary cameras are not effective for collecting naturalistic VRU-AV interaction data. Instead, researchers typically mount cameras on AVs [49, 50] to capture videos for subsequent analysis. In [51], the safety of interactions between AVs and pedestrians was assessed at three different locations in the US and Singapore by two different AV manufacturers.

2.3. VR Experiment to Study VRU-AV Interaction

This section reviews the VR experiments in transportation research. Section 2.3.1 introduces the VR experiment as a new data collection approach. Section 2.3.2 provides a general description of the diverse applications of VR in transportation research. Section 2.3.3 reviews the studies of VRU-AV interactions within VR experiments.

2.3.1. Virtual Reality Experiments

Recently, VR experiments have gained recognition as a powerful method for studying VRUs' behaviors [12, 13, 14]. By providing an immersive environment, VR enables participants to interact with virtual traffic scenarios like real-world situations, all while maintaining a high level of safety and collecting the necessary trajectory data. Several studies [52, 53] have also demonstrated that participant behavior in VR aligns closely with established real-world behavioral norms.

VR experiments offer several advantages over traditional data collection methods [12]. First, VR experiments are conducted in a controlled environment, making it easier to study the impact factors that researchers are interested in [13]. Second, unlike other controlled experiments, such as those conducted in real-life settings or fire evacuations, VR experiments are also free of safety and ethical concerns [54]. Additionally, VR experiments allow for the immersive exploration of proposed or futuristic scenarios that may be challenging to set up in traditional data collection methods [55].

Despite the increasing interest in using VR for road user behavior research, several research limitations still need to be addressed. One significant limitation is the question of generalizability to real-world settings [53], necessitating more validation studies to further confirm the method's reliability [54, 56]. Another challenge is the diversity and variability in simulator setup and fidelity, which can also affect consistency and outcomes across different experiments.

2.3.2. VR Applications in Transportation Research

An expanding body of research has utilized VR to investigate domains such as road-crossing behaviors [13, 14, 3], design evaluation [13, 34, 35, 57], choice behaviors [58, 54, 55], way-finding behaviors [59, 60], and educational training [61, 62, 63]. Each domain is discussed below:

Road Crossing

One of the most commonly studied areas utilizing VR in transportation research is road crossing behavior [3]. [13] investigated how the physical appearance of the AV and eHMI affect pedestrians' crossing intention. [14] also explored the main factors influencing cyclists' crossing intentions when interacting with an AV as compared to a conventional vehicle using a 360-degree video-based VR method. For more details on the VR research on pedestrian-AV interaction, see [3].

Design Evaluation

Since VR can let the participant immerse in a futuristic or hypothetical scenario, this feature can facilitate the researchers and designers to evaluate the design such as the eHMI equipped on the AVs [13, 34, 35] and the road infrastructure [57]. eHMI plays an important role in AVs and VRUs communicating and negotiating with each other. However, there is still no consensus on how to design an eHMI that may serve all road users successfully. VR experiment is a promising approach to facilitate the design and development of this process [34, 35, 13]. Similarly, the design of existing or concept infrastructure can be tested as well in VR to assess their functionalities. In [57], the cyclist's perceived safety was collected and rated via VR experiment and survey.

Choice Behavior

Choice behavior modeling presents a promising research domain for VR applications [58, 54, 55]. Stated preference surveys often face challenges due to their lack of realism [58], but VR can address this limitation by immersing participants in a virtual environment. For example, [58] constructed a hypothetical VR environment featuring AVs and related infrastructure changes on urban streets to investigate pedestrian preferences. This VR-based approach was also compared with two traditional methods—text-only and visual aids. The findings revealed that VR not only enhanced respondents' understanding of the scenarios but also produced more consistent results. In [54], pedestrian exit choice behavior during evacuation was examined using both VR and field experiments, with findings indicating that pedestrian exit choices in VR closely mirrored those observed in the field. Similarly, [55] explored the influence of lighting on pedestrian route choices through VR experiments.

Way-finding Behavior

Beyond road safety studies, pedestrian behaviors such as way-finding can also be effectively studied using VR [59, 60]. For instance, [59] evaluated the feasibility of using VR as a research tool to study way-finding behavior in complex multi-story buildings. [60] also developed a way-finding model that incorporates both spatial knowledge and visual information, based on data collected from VR experiments.

Education and Training

One promising application of VR is in education and training for VRUs such as children, and the elderly [61, 62, 63]. [61] conducted a behavioral intervention within a VR environment to address distracted pedestrian behavior. [62] utilized VR to provide child pedestrian safety training at schools and community centers. Additionally, [63] developed a VR-based training program to help older pedestrians make safer street-crossing decisions.

2.3.3. VR Experiments for VRU-AV Interaction

This section details the VR experiment studies involving AVs and their interactions with pedestrians, cyclists, and multiple participants, respectively.

Pedestrian-AV Interaction in VR Experiment

Numerous VR experiment studies involving AVs concentrate on their interactions with pedestrians. These studies cover aspects such as eHMI design [34, 64], road conditions [19, 65, 17], and driving styles [13, 66, 17].

VR experiment is an efficient and powerful approach to evaluate the effectiveness of different proposed eHMI designs. First, VR experiments enable the researchers to design more advanced eHMIs with multiple modalities [64] and let the participants experiment with them in a more immersive way [67], compared to other approaches such as online surveys [68], and field studies [6, 45]. For example, [64] investigated the effect of the combination of visual and audible eHMIs on the pedestrian-AV interaction process. In another study [67], the acceleration indication eHMI was assessed in particular to combine the explicit cue of eHMI and implicit cue of vehicle motion. Second, VR experiments allow researchers to investigate the effectiveness of eHMI designs from diverse perspectives [69, 34, 65]. In [34], a motion-based approach was proposed and assessed as a valid implicit investigation method for eHMI designs, aiming to complement the traditional questionnaire and explicit intention confirmation by pressing a button. Furthermore, in [65], the scalability issue of eHMI design was investigated when the AV encounters multiple pedestrians at the same time, which is hard to assess in other assessment approaches [69].

The investigation of road layouts [17, 19, 65] has also been carried out in several VR experimental studies. While the majority of VR studies focus on unsignalized traffic situations with one-lane roads [23, 65, 34] and two-lane roads [36, 22], some other road layouts have been investigated to study their effects on pedestrian-AV interactions. For example, the study by [65] examined how the median influences pedestrian safety and trust in AVs while crossing streets. Meanwhile, [17] compared T-junctions and straight roads to evaluate the effect of road layout on pedestrian crossings. Additionally, [19] compared five different street designs to assess practical interventions for managing collective behavior among pairs of pedestrians.

The AVs significantly impact the interaction between pedestrians and AVs, with kinematic factors such as speed, gap, and deceleration influencing pedestrian crossing behavior. For instance, the study in [13] controlled the speed and gap of a single AV to examine pedestrians' intentions to cross. Another study, [66], explored how these factors affected pedestrians' decisions when faced with a group of AVs. Additionally, [17] investigated how different deceleration profiles of AVs influenced pedestrian reactions to yield signals.

Cyclist-AV Interaction in VR Experiment

Compared to the popularity of using VR experiments to study the interaction between pedestrians and AVs, studies on cyclist-AV interaction are still scarce [14, 70]. This is due to the difficulty of designing and developing a cyclist simulator with VR headset [71, 72], compared to the pedestrian VR simulator.

eHMI design is investigated in one study [70]. The researchers implemented an immersive VR cyclist-simulator, and designed and evaluated several AV-cyclist interfaces. The results confirmed that AV-cyclist interfaces could improve cyclists' confidence in AV lane-merging scenarios.

In a different study [14], researchers used 360-degree VR video recordings to examine how cyclists decide when to cross paths with an AV and an HDV. By varying factors such as the type of vehicle, its speed, the size of the gap, and the right of way, the study explored how these elements, along with road conditions and driving styles, influenced cyclists' crossing decisions. The findings indicated that gap size and right of way were the main factors affecting cyclists' crossing intentions, while vehicle type and speed did not significantly impact their decisions.

Multi-player Interaction in VR Experiment

Although numerous VR experimental studies have been carried out in the literature, the majority involve only one participant interacting with computer-programmed characters [29]. The way participants behave when interacting with a real person can differ from their interactions with computer-generated characters. For instance, [73] observed notable differences in crossing behavior when participants crossed alongside another human participant compared to an NPC in a VR experiment.

Implementing a multi-player, multi-modal VR co-simulator presents several challenges: First, developing multi-player VR environments demands greater technical expertise to maintain stable connections and design dynamic interactions. Achieving a high level of realism is significantly more complex than achieving a high level of realism in single-user pedestrian VR applications, many of which are readily available and easy to use. Consequently, the development timeline for multi-player VR co-simulators is typically much longer. Second, creating VR simulations for other road users is generally more challenging than for pedestrians. Pedestrian-based VR applications remain the most commonly explored in VR research. In contrast, studies focusing on different road user types must build custom simulators tailored to those users, requiring considerable time and effort to ensure feasibility and validated results.

Hence, there is a scarcity of studies examining real-time human-to-human interactions among different types of road users. Only a limited number of studies have explored interactions between various road users [74, 22, 23]. For instance, [22, 23] developed a co-simulator to investigate vehicle-pedestrian interactions.

Furthermore, as highlighted in Section 2.1, group dynamics play a crucial role in shaping the road behaviors of pedestrians and cyclists. Incorporating multiple participants into VR as a group offers a promising approach to gaining deeper insights into this phenomenon. For example, [73, 17, 19, 20] involved two participants acting as pedestrians crossing the street together. A detailed summary of these studies is provided in Table 2.1.

Table 2.1: Summary of previous work on multi-player road-user simulators.

Paper	Year	#Players	Road Users Involved	Setup
[74]	2019	2+	Pedestrian-driver	VR headsets
[22]	2023	2	Pedestrian-driver	Driving simulator + CAVE
[23]	2024	2	Pedestrian-driver	Driving simulator + VR headset
[19]	2024	2	Double pedestrians-vehicle	VR headsets
[17]	2024	2	Double pedestrians-AV	2 VR headsets
[20]	2024	2	Double pedestrians-AV	2 VR headsets

2.4. Shared Space

2.4.1. Motivations and Concept

Many current studies concentrate on standard road settings like intersections [25, 28, 42], street roads [16], and bicycle lanes [75]. These types of road designs are built on the principle of *separation* [76], which is meant to enhance the safety of each group of road users by keeping them apart. However, this principle may not always be suitable as the separation of road users can also have unintended consequences. For instance, physical barriers and designated lanes might restrict the flexibility and adaptability of the road space, disrupting the connectivity

between living areas. Moreover, the principle of separation may not effectively address the complexities of urban environments where space is limited [77, 78].

Therefore, a more integrated approach that encourages shared use and mutual awareness among all road users might be more effective in enhancing overall safety and mobility. Shared space [77, 78] is an urban design approach that integrates multiple modes of transportation, such as pedestrians, cyclists, and vehicles, into the same area, without the conventional separation of road users through elements like traffic signals, road markings, or curbs [21]. There are a broad of attempts on this concept across several countries, such as Netherlands [17], United Kingdom [79], New Zealand [80], etc.

In shared space, the boundaries between different modes of transport are deliberately blurred to promote a more cohesive and flexible use of space. This design approach can enhance the aesthetic appeal of urban areas, create a more pleasant and engaging public realm, and strengthen the social fabric by encouraging people to share the same space harmoniously. Ultimately, the goal of shared space is to balance the needs of all users while creating a dynamic, adaptable, and inclusive urban environment that supports both mobility and community interaction.

2.4.2. Previous Study on Shared Space

Effectiveness

Shared space is often regarded as a modern trend in urban design, yet its effectiveness remains a subject of ongoing debate. Consequently, numerous studies [80, 21, 81] have been conducted to evaluate the impact of shared spaces by analyzing conditions before and after the implementation of shared space strategies.

[80] examined three shared space locations in Auckland, New Zealand, to evaluate their effectiveness in terms of pedestrian density and vehicle speed. The study found that, overall, mean vehicle speeds tended to decrease as pedestrian density increased within shared space zones. [21] also explored the impact of installing bike dismount signs within a shared space in Vancouver, Canada, analyzing cyclist compliance rates and the frequency of pedestrian-bike interactions. The findings highlighted the effectiveness of these signs in reducing pedestrian-cyclist conflicts. [81] analyzed the impact of the Pedestrian Priority Street Projects in Seoul, Korea, which incorporated innovative paving design techniques. The study found that these changes led to reduced vehicle speeds and improved perceptions of pedestrian safety.

Influence Factors

As the effectiveness of shared spaces becomes more widely recognized, some studies have shifted their focus to examining the factors that influence perception [82], safety [83], and behavioral and conflict analysis [84, 85, 86, 87] in shared space.

Regarding perception, [82] examined the factors influencing pedestrians' and drivers' perceptions in shared spaces through two separate web-based stated-preference surveys. For pedestrians, comfort in sharing space with vehicles was the measure, while for drivers, it was their willingness to share space with pedestrians. The study found that pedestrians are more comfortable when there are fewer vehicles, more pedestrians, and designated safe zones, with females and older pedestrians expressing less comfort. Drivers, especially those who encounter many pedestrians or children and elderly individuals, feel less confident, while male drivers and those with prior shared space experience are more willing to share. Additionally, good lighting was found to improve perceptions for both groups.

In terms of safety, [83] explored the relationship between expressed safety concerns and actual incidents experienced by travelers in a high-volume non-motorized shared space. The study also identified key factors contributing to pedestrian-cyclist incidents. Prior experience with incidents was found to be a significant factor influencing safety perceptions. Cyclists expressed concerns about inter-modal conflicts and safety similar to pedestrians and preferred to avoid pedestrian-dominated areas, although this preference was balanced against factors like travel time, ease of way-finding, and the desire to avoid motor vehicles. Both pedestrians and cyclists identified crowding and pedestrian inattention as major contributors to incidents, though they disagreed on whether cyclist speed played a role.

For behavioral and conflict analysis, [86] proposed a semi-automated framework for analyzing pedestrian-cyclist conflicts by extracting metrics from video recordings. Key findings revealed a negative correlation between speed and pedestrian density and a positive correlation between conflict rate and density. Statistical differences were also observed between conflict types, categorized by intersecting angles and road user configurations. [87] explored conflict behaviors and characteristics among pedestrians, conventional bicycles, and e-bikes in shared

spaces. E-bikes and pedestrians were found to have a higher occurrence of conflicts and crashes, with pedestrians facing greater injury risks.

2.4.3. VRU-AV Interaction in Shared Space

As AVs continue to advance and are increasingly integrated into real-world traffic, a critical challenge emerges: how to ensure safe and efficient interactions between AVs and various VRUs (such as pedestrians and cyclists) in shared spaces. Shared spaces, by removing traditional separation, encourage human drivers and VRUs to collaboratively resolve potential conflicts, fostering greater engagement. This requires AVs to emulate human driving behaviors and adhere to social norms [32]. Meanwhile, understanding how VRUs behave and interact with AVs is equally critical, therefore AVs will be able to understand the decision-making process and predict the future behaviors of VRUs.

Despite the growing interest in shared spaces, research on VRU-AV interactions in these environments remains limited, largely due to the challenges of observing real-world interactions between AVs and VRUs.

Some studies [32, 88] have sought to infer potential pedestrian behaviors by examining interactions with various types of vehicles, including mobile robots. [32] reviewed pedestrian behaviors when interacting with conventional cars, mobile robots, and AVs, highlighting the diversity and imperfections in pedestrian actions. This underscores the need for AVs to account for such behavioral variability and adhere to socially compliant rules to gain pedestrian understanding and acceptance. Similarly, [88] analyzed video data from a naturalistic driving dataset to investigate pedestrian responses to AV-like vehicles in shared spaces, identifying key reactions and behaviors in these settings. While preliminary assumptions can be drawn from human interactions with other types of vehicles, how VRUs would engage with AVs in shared spaces remains uncertain.

One approach is to conduct live demonstrations for road users to engage with, which is largely used to assess the design of eHMI for AVs [89]. In [90], 664 participants completed a questionnaire about Level-4 AVs during live demonstrations in three European cities. The study explored pedestrians' and cyclists' perceptions of safety and their opinions on the types of information that should be displayed on AVs. [91] conducted an online study to investigate how pedestrians interact with two types of automated vehicles (AVs), specifically a car and a bus, within shared spaces. Both vehicles utilized identical eHMI communication strategies, including mode awareness, intention-based, perception-based, and a combined approach, implemented via an LED light band. The findings revealed that participants felt significantly safer and more at ease when interacting with the car compared to the bus. Additionally, participants reported feeling substantially safer and better informed when any eHMI communication strategy was used, compared to mode awareness alone or the absence of eHMI, across both vehicle types. Besides eHMI design, [31] explored the willingness to cross in front of an AV, the feeling of security, and the feeling of relaxation among 254 cyclists and pedestrians in Australia and the UK, through an online questionnaire.

VR has also been utilized to investigate VRU-AV interactions in shared spaces [17, 92]. [17] studied pedestrian-AV interactions in these environments, where participants attempted to cross the road under varying conditions, including the presence of another pedestrian, different eHMIs, AV driving styles, and road conditions. In a separate study, [92] examined the behavior of elderly Japanese pedestrians interacting with an AV in a shared space using a CAVE-based VR experiment. [93] investigated the design of eHMIs for different types of AVs for the interaction with pedestrians in shared space.

2.5. Summary

The literature review reveals numerous research into the road behaviors and interactions of VRUs, employing a range of data collection methods. In recent years, immersive VR experiments have become a popular tool for transportation research, especially effectively in investigating VRUs' behaviors and their interactions with AVs.

To summarize, two key research gaps have emerged from this review: First, there is a need for an advanced VR co-simulator capable of supporting multi-player, multi-modal VRU-AV interactions. Second, studies on VRU-AV complex interactions involving multiple road users within shared spaces are scarce.

3

Simulator Development

This chapter highlights several essential features of the developed multi-player, multi-modal VR co-simulator. Section 3.1 begins by detailing the simulator integration, which allows pedestrians and cyclists to engage within the same virtual environment. Next, Section 3.2 discusses the development of body-tracking and road user avatars to enable realistic representations and interactions of road users. Finally, Section 3.3 covers the various methods and sources for data collection utilized within the VR co-simulator, ensuring a comprehensive and diverse dataset for analysis and further development.

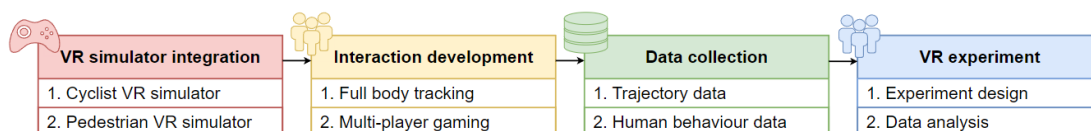


Figure 3.1: Overview of the VR co-simulator development.

Together, these elements contribute to the VR co-simulator’s advanced capabilities in creating engaging and interactive virtual environments, as shown in Figure 3.1.

3.1. Simulator Integration

This section answers the first sub-research questions in Section 1.4.2 regarding the simulator integration and outlines the steps involved in integrating different current VR simulators, starting with an introduction to the existing VR simulators for pedestrians and cyclists. It then explores the implementation of multi-player functionality, detailing the setup of a basic multi-player VR system.

3.1.1. Existing Simulators

The first step in designing and developing this multi-player multi-modal VR co-simulator is to integrate the currently available pedestrian and cyclist VR simulators. The VR simulators used to integrate into the co-simulator are shown in Figure 3.2, respectively. These dedicated VR simulators were designed and developed by The Mobility in the eXtended Reality Lab (MXR Lab) of TU Delft for the research of pedestrian and cyclist behaviors [17].

The pedestrian VR simulator offers players two different methods of locomotion. They can use a motion controller to teleport to different locations within the virtual environment. Alternatively, participants can opt for the free-hand locomotion method to navigate the virtual space more freely.

The bike VR simulator uses a stationary setup to replicate the cycling experience for cyclists on the road. This system includes a Garmin TacX Flow bike trainer, an actual bicycle, and a Raspberry Pi, which captures real-time speed and braking inputs.

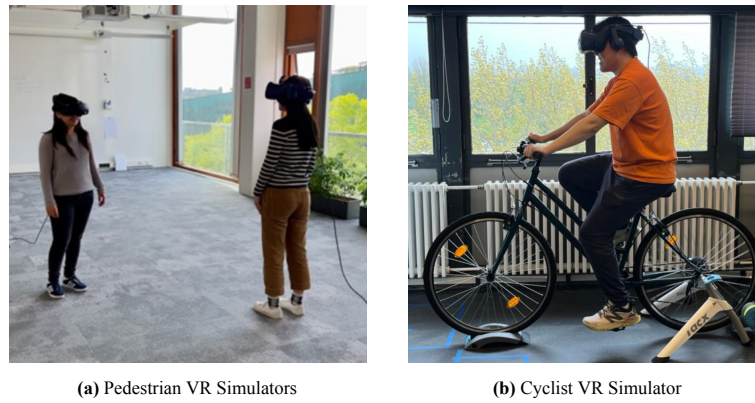


Figure 3.2: The existing pedestrian and cyclist VR simulators in the MXR Lab.

3.1.2. Multi-player

The VR co-simulator has been developed utilizing Unreal Engine 5 (UE5), a powerful computer gaming engine. UE5 offers integrated support for multi-player gaming, enabling developers to build interactive experiences where multiple players can engage simultaneously in a shared virtual environment.

Server-client Architecture

In UE5, two server-client architectures are available for multi-player games, namely listen servers and dedicated servers.

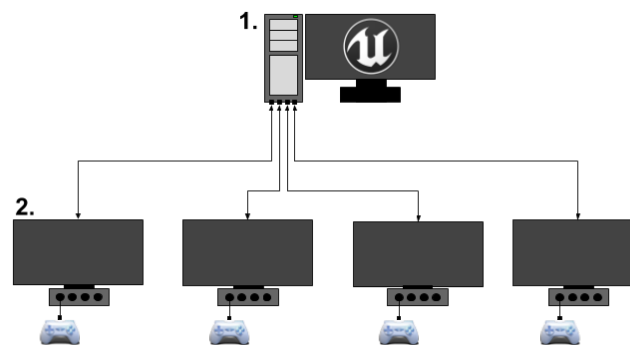


Figure 3.3: Illustration of the networked multi-player architecture in UE5.

A listen server allows one player to act as both the server host and a player in the game on the same machine. It is easy to set up and is suitable for small-scale games or casual multi-player experiences. However, the host player has an advantage due to direct access to the server, and the system may struggle with heavy processing loads as it handles both server and player functions.

In contrast, a dedicated Server is hosted on a separate machine that does not participate in the game as a player. It ensures fair gameplay for all connected players and handles large-scale or high-performance games efficiently by focusing solely on game logic and networking. However, it requires additional resources and configuration.

In this way, we choose to use the listen server server-client architecture for the current implementation because it is simple to configure and allows for spontaneous setup. This suits small-scale VR experiments and cooperative gameplay among a limited number of participants, where fairness and heavy network loads are not critical concerns.

Replication

Replication is a key concept in multi-player game development, referring to the process where the authoritative server transmits state data to connected clients. As mentioned earlier, the server maintains the true game state. Clients replicate this state locally, enabling them to render graphics and audio, communicate with other clients, and

engage in gameplay. Properly configured replication ensures synchronization across game instances on different machines, allowing for seamless gameplay.

To achieve a realistic VR co-simulator, implementing replication between the server and clients is essential to ensure synchronization across different instances. Beyond the basic synchronization of player and object locations and rotations within the virtual environment, replication must also account for more complex and dynamic data. This includes detailed body movement data, such as joint positions and orientations, which are critical for accurately reflecting player actions in real time. Additionally, replication must handle eye-tracking data, ensuring that gaze behavior is consistently represented across all clients. This level of detailed synchronization is crucial for creating an immersive and interactive VR experience, as it allows participants to engage with the virtual environment and with one another cohesively and realistically.

3.2. Interaction Development

This section answers the second sub-research question in Section 1.4.2. First, we introduce how the body tracking systems for pedestrians and cyclists in VR are designed, respectively. Then, we show how a more realistic human-being representation is displayed in VR via the technique called *MetaHuman*.

3.2.1. Body Tracking

The body tracking system is essential for achieving real-time, accurate representations of road users' movements and behaviors. By capturing and reproducing natural motion, body-tracking technology enables dynamic and interactive simulations, allowing participants to interact authentically with the virtual environment. Section 3.2.1 introduces the full-body tracking system used for pedestrians, which serves as the foundational framework. Building upon this, Section 3.2.1 outlines the upper-body tracking system developed specifically for cyclists.

Pedestrian Full Body Tracking

To accurately simulate realistic behaviors and interactions among different road users in VR, the priority is to ensure a precise representation of body movements within the virtual environment. Consequently, we implemented a full-body tracking system for pedestrians as the foundational framework for other road users.

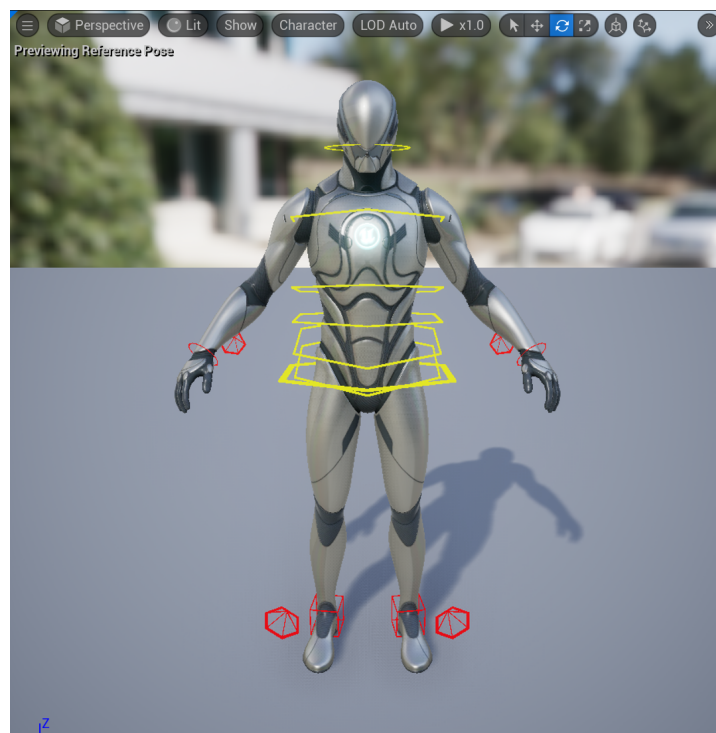


Figure 3.4: The pedestrian full-body tracking.

As illustrated in Figure 3.4, the full-body tracking system for pedestrians captures the movement of their head, hands, waist, and feet. This system can be broken down into several components: head, spine (waist), hands,

and feet. For the head, a VR headset tracks its position and orientation, making it the simplest element of the implementation. This is represented by the yellow circle around the avatar's head. Spine movement is tracked using a single tracker, which controls the overall movement of the spine. The motion originates from the tracker at the bottom, represented by the yellow hexagon, and propagates upward through the spine. The hands and feet are tracked using inverse kinematics, enabling precise representation of their movements within the VR environment.

Cyclist Upper Body Tracking



Figure 3.5: The cyclist upper-body tracking.

The cyclist body-tracking system builds upon the pedestrian full-body implementation but focuses solely on the upper body, as the feet typically remain on the pedals. As a result, the cyclist's animation combines real-time tracking with pre-defined animations.

A key distinction between cyclist and pedestrian tracking is the requirement for cyclists to grip the bike's handlebars, ensuring they appear to be cycling rather than floating. To achieve this, the hand-mounted trackers are used to monitor whether the hands are in contact with the handlebars.

3.2.2. MetaHuman

Along with utilizing body tracking to replicate the dynamic movements of road users, it is equally crucial to give them a lifelike human appearance when they are introduced into the VR environment. As shown in Figure [3.6](#) presents a technology called MetaHuman, which is used to fulfill this requirement.

This feature has several advantages as follows:

- **Realism**

MetaHuman in UE5 stands out for its unparalleled realism. It provides high-fidelity 3D human characters that are photorealistic and ready to use. The detailed textures, advanced skin shaders, and lifelike animations make it ideal for applications like films, games, and simulations. With facial rigging and motion capture compatibility, the MetaHuman system delivers expressive and authentic human appearances.

- **Customizability**

MetaHuman Creator offers users the ability to tailor every detail of a character. You can adjust features such as facial structure, skin tone, eye color, hairstyle, and body proportions with precision. The tool also



Figure 3.6: The MetaHuman characters used in the VR co-simulator.

allows mixing features from existing templates, enabling users to design unique characters that fit their artistic or narrative needs.

- **Hierarchical Body Meshes**

MetaHuman characters are built with a hierarchical body mesh system, enabling optimization and scalability. The mesh structure supports various levels of detail, making it suitable for diverse performance requirements. From detailed close-ups to distant crowd simulations, the hierarchical system ensures efficient rendering without compromising visual quality.

Despite its strengths, using MetaHuman in VR at the highest level of detail remains challenging. The computational demands for rendering full-fidelity MetaHuman in real-time VR environments often exceed the capabilities of most systems, limiting their applicability for high-quality immersive experiences.

3.3. Data Collection

The ultimate goal of establishing this VR co-simulator is to gather data on the behaviors and interactions of different road users via the VR experiments. We highlight the trajectory and behavioral data that the VR simulator is capable of collecting, respectively.

3.3.1. Trajectory Data

Trajectories include the fundamental information about the road users' behaviors [46]. A collection of the important objective metrics can be derived from the trajectory data. Therefore, the VR co-simulator should be able to save the trajectory data.

In the implementation, the trajectory data is collected to precisely track the positions and movements of participants throughout the virtual environment. This data set includes real-time updates of spatial coordinates and velocities, ensuring an accurate depiction of both pedestrian and cyclist paths. The data is sampled at a high frequency to maintain a detailed and reliable record of movement patterns.

3.3.2. Behavioral Data

Besides trajectory data, more VRUs' behavioral data can be gathered via VR experiments and provide more insights into the VRUs' decision-making process. As [4] reported, VRUs also reply on implicit communications, such as eye contact and gestures to negotiate with the vehicles. Furthermore, [15] confirmed that body movement can also be linked with the pedestrians' decision-making process. Therefore, it is beneficial to consider including these behavioral data in the data collection framework of the VR co-simulator.

The HTC Vive Pro Eye VR headset, equipped with integrated eye-tracking technology, provides detailed insights into participants' visual attention. The system records data such as gaze origin and direction, enabling researchers to identify specific objects or elements participants focus on during interactions in the virtual environment. While the device is capable of collecting additional information, such as pupil diameter and blink status, these data are currently inaccessible within UE5. As a result, this portion of eye-tracking data will not be included in the upcoming VR experiment.

The body-tracking system detailed in Section 3.2.1 enables the collection and storage of comprehensive movement data for pedestrians and cyclists. This system records the precise spatial coordinates and orientation of each tracker used in the VR simulator. The spatial data includes x, y, and z positions measured in centimeters, while orientation is captured as pitch, yaw, and roll angles in degrees. For pedestrians, six trackers are utilized to monitor the entire body, including the head, waist, hands, and feet. For cyclists, the focus is on the upper body, with trackers placed on the head and hands.

4

Methodology

This study utilized immersive VR experiments as a case study to demonstrate the capability of a multi-player, multi-modal VR co-simulator for investigating the behaviors and interactions among various road users. Specifically, the VR experiment explored interactions in a shared space environment between VRUs, such as pedestrians and cyclists, and AVs.

Section 4.1 outlines the experimental design, including the scenario under study, key factors, and participant tasks. Section 4.2 details the equipment utilized in the experiment. Section 4.3 provides a comprehensive explanation of the experimental procedure. Data collection methods and data analysis approaches are described in Sections 4.4 and 4.5, respectively. Finally, Section 4.6 presents the demographic and other characteristics of the recruited participants.

4.1. Experimental Design

This VR experiment has two aims. First, the design and development of the multi-player, multi-modal VR Co-simulator are assessed. Second, the effect of the role of VRUs, the number of VRUs, and the initial location of VRUs on the VRUs' behaviors and their interactions with the AV in the shared space is investigated. A within-subject design approach was used in the current study to remove the effects of individual differences.

4.1.1. Experiment Scenario Design



Figure 4.1: The real-world shared space scenario used as a reference.

One existing shared space, intersected by the Oude Langendijk and the Jacob Gerritstraat near the New Church in Delft, The Netherlands, was chosen and modified to construct the VR environment. The bird-eye view and street view of the reference site are shown in Figure 4.1, respectively. In this shared space environment, there were no traffic lights, no stop signs, no pedestrian zebra, or any other elements to indicate the right of way. An audio soundscape was added to the VR environment to enhance the realism of the VR experience. The landscape



Figure 4.2: The eye-bird view of the established VR scenario.
The green and blue circles indicate the farther and closer starting location.
The orange bar indicates the destination of the crossing.

of the established VR scenario is shown in Figure 4.2. In Figure, the green and blue circles indicate the farther and closer starting location, respectively. The orange bar indicates the destination of the crossing.

4.1.2. Experiment Factors

Three within-subject variables were included in this VR experiment: the number of VRUs (i.e., 1, 2), the role of VRUs (i.e., pedestrian or cyclist), and the initial location relative to the AV (i.e., far away or close to the AV), as summarized in Table 4.1. A detailed description of each variable is provided below.

Table 4.1: Variables included in this experiment

Variable name	Levels	Annotation	Explanation
#VRU	2	1	Single-player trial
		2	Double-player trial
Role of VRU	2	Ped	Participant plays as a pedestrian
		Cyc	Participant plays as a cyclist
Initial Location	2	Far	VRU starts far away from the AV
		Close	VRU starts close to the AV

Number of VRUs

Based on the research question, this study aims to explore the interaction between multiple real human road users through VR. To achieve this, both single-VRU and multiple-VRU crossing tasks were developed. In the single-VRU crossing task, participants take on the role of either a pedestrian or a cyclist. In the multiple-VRU crossing task, two participants cross the street together.

Role of VRUs

In addition to the number of VRUs, participants cross the street in distinct roles. Pedestrians and cyclists, as common road users in shared spaces, are included in the experiment. In the single-VRU tasks, participants take turns playing as a pedestrian and a cyclist. In the multiple-VRU tasks, two participants cross the street together, either as two pedestrians or as one pedestrian and one cyclist.

Relative Location to AV

Since the shared space being studied is a relatively narrow street with a width of about 5 meters, visibility is a common concern. To explore the impact of relative locations of VRUs on the interaction between VRUs and AV, the distance gap was included as the final variable to manipulate in the experiment. In the single-VRU experiment, participants start from two different positions, located 1.5 meters to the left and right of the street's centerline. In

the multiple-VRU experiment, the two participants start from the same positions as in the single-player scenario, maintaining an initial distance of 3 meters between them. Initially, a 4-meter distance between the two VRUs was selected to balance avoiding proximity that could encourage group behavior, while still ensuring that the eHMI yielding message would be relevant to both pedestrians, following the approach of [17]. However, this distance was later reduced to 3 meters to ensure safe walking movement within the experiment room while using VR, as the room is 5 meters wide and equipped with base stations mounted on tripods along the walls and windows side.

4.1.3. Experiment Task Design

The combination of all variables led to a total of 10 road-crossing scenarios, which were organized into four blocks, as shown in Table 4.2.

Table 4.2: Tasks and blocks included in the VR experiment.

Task	Block	#VRU	Role of VRU	Initial Location
1	I	1	Ped	Far
2		1	Ped	Close
3	II	1	Cyc	Far
4		1	Cyc	Close
5	III	2	Ped⊕Ped	Far⊕Close
6		2	Ped⊕Ped	Close⊕Far
7	IV	2	Ped⊕Cyc	Far⊕Close
8		2	Ped⊕Cyc	Close⊕Far
9		2	Cyc⊕Ped	Far⊕Close
10		2	Cyc⊕Ped	Close⊕Far

Ped denotes pedestrian.

Cyc denotes cyclist.

Far denotes the starting location far away from AV.

Close denotes the starting location close to AV.

⊕ serves as the delimiter, with the symbol before representing player 1 and the symbol after representing player 2.

Block I (Single Pedestrian Crossing)

This block comprises two single-pedestrian crossing scenarios. These scenarios are designed to investigate the behaviors of pedestrians as they navigate the street from distinct starting positions. This allows for a detailed analysis of decision-making processes in urban environments, particularly focusing on individual pedestrian actions.

Block II (Single Cyclist Crossing)

This block features two single-cyclist crossing scenarios, which aim to examine the crossing behaviors of cyclists at intersections. Similar to Block I, the scenarios emphasize the independent crossing experiences of cyclists, providing insights into their specific interactions with the environment.

Block III (Dual Pedestrian Crossing)

This block includes two double-pedestrian crossing scenarios. In these scenarios, two pedestrians cross the street concurrently, facilitating an exploration of their interactions and the subsequent effects on their decision-making processes. This block aims to elucidate the dynamics of pedestrian interactions in shared spaces.

Block IV (Pedestrian-cyclist Joint Crossing)

This block focuses on pedestrian-cyclist joint crossing scenarios. In these scenarios, both pedestrians and cyclists engage in crossing the street simultaneously, thereby allowing for an examination of the interactions and responses among different road users in a mixed-use context.

The scenarios differed only in the within-subject variables, while the rest of the environment, such as infrastructure, surrounding buildings, and sounds, remained unchanged. In all blocks, the AV consistently yielded to participants, although this behavior was not explicitly communicated to them.

AV Setup

Besides participants, AV setup is also important for the experiment design. In all scenarios, the AV started to approach the pedestrian from 30 meters away at a speed of 15 km/h following the speed limit of shared space in the Netherlands.

The deceleration profile involved only a single phase of deceleration. When the distance between the AV and the VRU reaches 15 meters, the AV begins to decelerate from 15 km/h to 5 km/h at a rate of 2.5 m/s^2 and then continues at 5 km/h. The AV comes to a complete stop 3 meters away from the pedestrians. This deceleration style was also employed in a previous study [17] to examine how deceleration affects pedestrian crossing behaviors. It is considered more effective because it is defensive, allowing the early braking to better communicate the AV's yielding intention, thereby reducing pedestrians' decision time to cross the road.

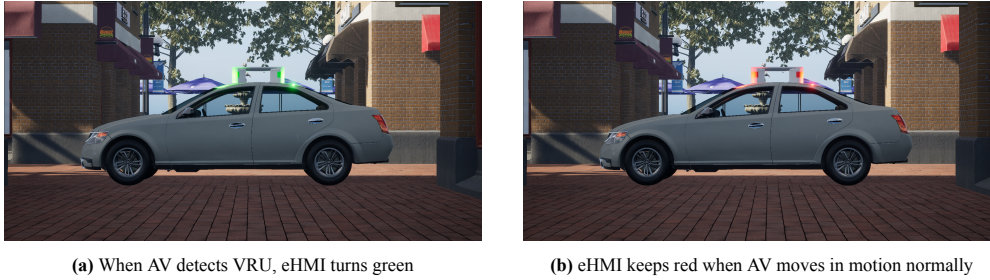


Figure 4.3: The AV with a light-based eHMI design.

To further indicate that the approaching vehicle is an AV, an eHMI has been specifically designed on top of the vehicle to convey its intentions. The eHMI is light-based. When the light turns green, it indicates that the AV has detected the VRU and is willing to yield the right of way. Conversely, a red light signifies the opposite. The appearance of the AV with eHMI is illustrated in Figure 4.3.

4.2. Experimental Apparatus

4.2.1. Room Setup



Figure 4.4: Experimental setup in Room 6.98, Faculty of Civil Engineering and Geosciences, TU Delft.

The VR experiment was conducted in Mobility in eXtended Reality Lab (MXR Lab), Room 6.98, within the

Faculty of Civil Engineering and Geosciences at TU Delft, from Monday, October 14th to Friday, October 26th, 2024. The room measured approximately 11 meters in length, 5 meters in width, and 3 meters in height. It was split into two sections, each simulating a crossing scenario for pedestrians and cyclists. All four blocks of VR experiments were held in this single room. Figure 4.4 illustrates the room layout for the VR experiment.

4.2.2. VR Hardware

To provide the VR experience and enable interaction during the experiment, two HTC Vive Pro Eye headsets (Resolution: 1440×1600 pixels per eye, 2880×1600 pixels combined, Field of view: 110 degrees, Refresh rate: 90 Hz) along with their standard motion controllers were used. Three Vive Tracker 3.0 devices were attached to different body parts of each participant for body tracking.

To allow unrestricted movement within the room, each headset was equipped with a wireless adapter, enabling a wireless connection, while the link boxes were connected to the workstation PC positioned in the corner of the room. Six base stations were strategically placed around the perimeter to ensure full tracking coverage of both the headsets and body trackers.

The two headsets were wirelessly connected to two separate Windows 10 desktops. Each desktop was equipped with an AMD Ryzen 9 7900X 12-Core Processor, 32 GB of RAM, an NVIDIA GeForce RTX 4090 graphics card, and a Samsung 990 PRO 4 TB SSD.



Figure 4.5: VR devices used in the VR experiment.

4.2.3. VR Software

To experiment, several additional software components are needed to support the co-simulator: SteamVR, developed by Valve, is a comprehensive VR platform that manages tracking, rendering, and device management, ensuring a smooth VR experience. VIVE Wireless supports the VIVE Wireless Adapter, handling wireless pairing, monitoring signal strength, and optimizing performance for a seamless, untethered setup. VIVE SRAnipel is used specifically for eye-tracking with the HTC VIVE Pro Eye. Combined with the UE5 co-simulator, these components form a robust system for effectively running the experiment and delivering an immersive virtual reality experience.

4.2.4. VR Co-Simulator Locomotion

In this study, we used a real-walking locomotion method, enabling participants to physically walk and rotate in the real world, with their movements mapped directly onto the virtual environment at a 1:1 scale. This allowed participants to naturally navigate the virtual space by walking in the real environment. Research [94, 95, 96] shows that real-walking locomotion leads to the more realistic and natural movement and enhances the sense of presence compared to other VR locomotion techniques.

The cyclist VR simulator features a stationary setup, a common approach for simulating cycling in virtual environments. It includes a Garmin TacX Flow bike trainer, a real bicycle, and a Raspberry Pi that measures the rear wheel's speed to record real-time cycling data. While participants can pedal forward and control their speed, steering is not supported, meaning they can only move forward in the virtual environment.

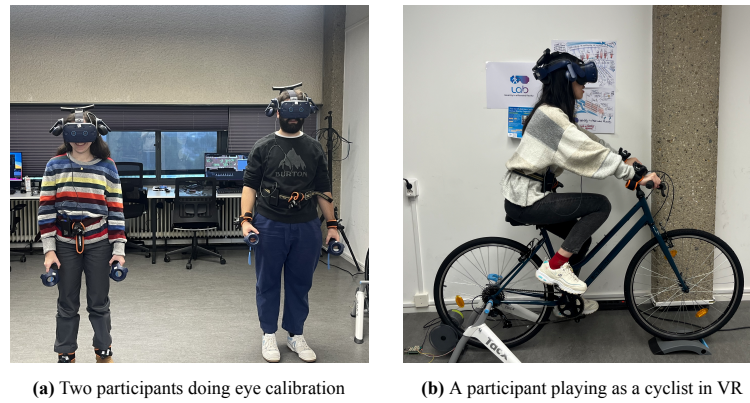


Figure 4.6: The locomotion of pedestrian and cyclist VR simulators.

4.3. Experiment Procedure

The VR experiment procedure comprises four distinct stages, namely, (1) introduction of the experiment, (2) calibration and familiarization with the VR locomotion, (3) official experiment, and (4) filling in the post-questionnaire. The following sections provide a more detailed explanation of these four stages:

4.3.1. Introduction

The first part involves providing participants with a brief introduction to the study. Each participant was required to sign individual consent forms and explicit consent points. Additionally, they were asked about their previous experience with VR and reminded of the potential for motion sickness. Participants were informed that they could request a break or stop the experiment at any time if they felt uncomfortable. Finally, we introduced them to the research background and the experiment's procedures, including the basic concept of shared space, the design, and the indication of the eHMI on AV.

4.3.2. Calibration and Familiarization

The second part is divided into two sub-phases: calibration and familiarization. Initially, participants were instructed to undergo a series of calibrations for eye-tracking, body-tracking, and bike handlebar adjustments. Once they successfully passed the calibration, they proceeded to a practice session to familiarize themselves with the locomotion in VR, as described in Section [4.2.4](#). Each sub-phase is detailed below:

Calibration

Each participant was assigned a desktop PC, a VR headset, a pair of motion controllers, and a set of 3 trackers throughout the calibration and familiarization phase and the following formal VR experiment. The two participants were instructed on how to properly wear the VR headset, motion controllers, and trackers via straps and belts. Detailed instructions on how to wear these devices can be viewed in the previous Section.

Participants began by performing the eye-tracking calibration using the headset's built-in calibration software. During this process, they were instructed to adjust the headset's position relative to their eyes and inter-pupil distance to ensure accurate tracking performance. Next, they were asked to trace a moving blue dot in VR while keeping their head still. Once the calibration was completed successfully, a test session was initiated to verify its accuracy. After this calibration session, participants were instructed not to adjust the headset to maintain consistency in the calibration.

Next, participants calibrated their avatar's body in VR according to their heights, using a body-copied character in front of them to inspect the results of the body tracking. They were allowed to adjust the orientation and position of their trackers until they were satisfied with their virtual representation in the VR environment. For cyclists, an additional step was required to ensure that participants could successfully grip the handlebars in both the real world and VR simultaneously, as the size and model of the bicycle differed slightly between the two environments.

Familiarization

After the calibration, participants were allowed to walk around the room or ride straightforwardly within the current level to become familiar with the VR locomotion mechanics as either pedestrians or cyclists. During this familiarization phase, there were no other pedestrians, cyclists, or vehicles present. Once participants felt familiar and confident with the new locomotion mechanics, they were moved on to the formal experiment levels.

4.3.3. Official Experiment

After the familiarization phase, participants were instructed to stand at a predefined location marked by a blue circle on the ground in VR, facing the correct direction. After each scenario, participants were required to return to their designated location before the next scenario began. Once the first two blocks (single-player scenarios) were completed, both participants proceeded to the last two blocks (multi-player scenarios).

4.3.4. Post-questionnaire

After completing the VR experiment, participants were instructed to remove the headset, motion controllers, and trackers, followed by a short break. They were then asked to fill out a post-experiment questionnaire to evaluate the simulator's design and assess their interactions with other agents during the crossing. Completing the post-experiment questionnaire typically took around 10 to 15 minutes. The purpose and application of each questionnaire are detailed in Section 4.4.2. The response rate for all surveys was 100%.

4.4. Data collection

Two types of data were collected during the experiment: Objective data (including movement trajectory, eye gaze, and body tracking) and subjective data (including questionnaire responses). These data are further elaborated as follows:

4.4.1. Objective Data

Throughout the formal experiment, the experimental software continuously captured and logged various objective measurements in real-time. These included participants' movement paths, eye movements, and body positions. All this data was automatically stored in the CSV file format for subsequent analysis. All data were captured at an approximate frequency of 40 Hz. The detailed information of this category of data is described in Section 3.3.

4.4.2. Subjective Data

There are eight sections in the post-experiment questionnaire. The eight sections cover the participant information, system usability [97], simulator sickness [98], realism [99], presence [100], trust in AV [101], perceived behavior control and risk [13], and feedback. The results of the questionnaires will be compared with the previous study [17].

4.5. Data Analysis

4.5.1. Metrics Definitions

The following metrics are calculated based on the three categories of datasets:

- Negotiation time $T_{negotiation}$ (s) is the period a VRU remains in negotiation before starting to cross, beginning from the moment the experiment is triggered (when the player presses the button on the motion controller to start the game).
- Crossing time $T_{crossing}$ (s) is defined as the duration for the VRU to reach the other side of the road from the moment they begin crossing.
- Space gap D_{gap} (m) is the longitudinal distance between the AV and the VRU when the VRU starts to cross.
- Total distance D_{total} (m), refers to the entire distance covered by the VRU during the road crossing.
- Average speed V_{total} (m/s) is the mean speed during the task, calculated by dividing the total traveling distance by the total traveling time.
- AV-gazing time T_{AV} (s), is aggregated by the collected eye-gazing data and means the total duration of gazing on the AV during the whole crossing process.

4.5.2. Model Formulation

The linear mixed model (LMM) was employed to study the influence of the selected factors including the VRU combination and starting location on the crossing behavior of different VRUs, based on the processed objective measures. LMM is particularly advantageous in accounting for both fixed effects, such as experimental conditions, and random effects, such as individual variability and repeated measurements within subjects, making it well-suited for analyzing complex, hierarchical data structures.

$$\begin{aligned}
 T_{negotiation}/T_{crossing}/D_{gap}/V_{total}/D_{total}^{ped}/T_{AV}^{ped} \\
 \sim \mu_{Block} + \mu_{Loc} + \\
 \mu_{Block} \times \mu_{Loc} + \\
 (1 | \psi_{pair}) + (1 | \psi_{pair} : \psi_{player})
 \end{aligned} \tag{4.1}$$

Dependent Variables

The model formulations of LMM were defined in Equation 4.1 using Wilkinson notation [102]. Several dependent variables, namely negotiation time $T_{negotiation}$, crossing time $T_{crossing}$, space gap D_{gap} , average speed V_{total} , total walking distance D_{total}^{ped} , and AV-gazing time T_{AV}^{ped} were modeled separately, as shown in the first row of the Equation 4.1. Dependent variables without the superscript *ped* refer to separate versions modeled for pedestrians and cyclists. The total walking distance and AV-gazing time were calculated exclusively for pedestrians, with the indication of the superscript *ped*. This is because cyclists, who cannot steer, have uniform distances, and the sample size (around 10 in the fourth block) for their eye-gazing data is insufficient.

Fixed Effects

The LMM is formulated as a function of the VRU combination μ_{Block} , the starting location μ_{Loc} , and the interaction term between μ_{Block} and μ_{Loc} , which are included as fixed effects in the model, as shown in the second and third rows of Equation 4.1. The levels of the variable μ_{Block} differ in the LMM based on the role of the road users (pedestrians or cyclists). For pedestrian-related metrics, the VRU combination μ_{Block} has three levels, corresponding to Blocks 1, 3, and 4 in the VR experiment, with Block 1 (single-pedestrian crossing) serving as the reference level. For cyclist-related metrics, there are only two levels, as participants acted as cyclists exclusively in Blocks 2 and 4, with Block 2 (single-cyclist crossing) as the reference level. The variable μ_{Loc} represents the starting locations of the VRU in each task, indicating whether they began closer to or farther from the AV. This variable μ_{Loc} retains two levels in both pedestrian and cyclist LMM formulations and the starting location farther from the AV is the reference level.

Random Effects

In addition, random effects were included to account for the complex data structures introduced by the multi-player experimental design. Both the pair ID ψ_{pair} and player ID ψ_{player} are taken into account, as shown in the last line of Equation 4.1. Specifically, the first random-effect term $(1 | \psi_{pair})$ accounts for the variability between different pairs of two participants. Since each pair may have unique characteristics that affect their crossing behavior, this random effect helps capture the inter-pair variability. And the second random-effect term $(1 | \psi_{pair} : \psi_{player})$ accounts for the variability within individual players in each pair. This term allows for modeling the fact that players within the same pair might exhibit different behaviors, thus capturing the intra-pair variability.

Program Environment

The statistical modeling and analysis were performed using the R programming language (Version 4.4.1) along with the `lmerTest` package (Version 3.1-3) to fit the LMM and `ranova` to report the p-values for random effects. All models were fitted using the maximum likelihood estimation method.

4.6. Participants

Participants were recruited using three approaches: (1) sharing information through various social media platforms, including LinkedIn, WhatsApp, and WeChat; (2) sending announcements via departmental email lists managed by secretaries from different faculties at TU Delft; and (3) distributing flyers placed around the TU Delft campus.

Participants had two options for joining the VR experiment: they could either participate as a pair with a friend or colleague, or they could choose to participate individually, in which case they would be paired with an unfamiliar

participant. The participant did not receive any compensation for their participation in the study. The study was approved by the Human Research Ethics Committee of the Delft University of Technology (Reference ID: 4607).

40 participants (20 pairs) took part in the VR experiment. All participants had normal or corrected vision and normal mobility. All participants' characteristics are shown in Table [A.1](#). No participants withdrew from the experiment due to motion sickness. In the end, 40 participants all finished both single-pedestrian and single-cyclist blocks. Unfortunately, two scenarios in the multi-player blocks were not conducted due to a failure of the VR devices.

5

Results

This chapter presents the results of objective and subjective measures collected from the VR experiment. Section 5.1 outlines the datasets and provides a preliminary descriptive analysis. Section 5.2 models the objective metrics using the LMM. Section 5.3 examines the subjective measures derived from the post-experiment questionnaire.

5.1. Dataset Summary

5.1.1. Sample Size

Objective data collected from the VR experiment include trajectory data, body-tracking data, and eye-gaze data. Table 5.1 summarizes the sample sizes for each data category across pedestrians and cyclists.

Table 5.1: Sample sizes for the trajectory, body-tracking, and eye-gazing datasets.

Role of VRU	Combination	Initial Location	Sample Size		
			Trajectory	Body-tracking	Eye-gazing
Pedestrian	Block 1	Far	40	40	31
		Close	40	40	33
	Block 3	Far	39	39	29
		Close	39	39	29
	Block 4	Far	38	38	28
		Close	39	39	29
	Overall	Overall	235	235	179
Cyclist	Block 2	Far	40	40	24
		Close	40	40	21
	Block 4	Far	39	39	11
		Close	38	38	10
	Overall	Overall	157	157	66

During the formal experiment, all participants participated in the single-player scenarios (blocks 1 and 2). However, in the double-pedestrian crossing scenario (block 3), data for one pair of participants were not recorded due to a base station detection failure. Additionally, one pair of participants did not complete the final block (block 4) of the pedestrian-cyclist joint crossing tasks due to time constraints. As a result, the trajectory and body-tracking datasets comprise 392 samples, including 235 pedestrian trajectories and 157 cyclist trajectories.

Eye-tracking data was also collected during the VR experiment. However, due to hardware and software issues, some participants' eye-tracking data were not successfully recorded or saved. Nonetheless, the remaining dataset, comprising approximately 30 pedestrians, is still sufficient for studying pedestrian eye-gazing behaviors during crossing in the shared space. In contrast, most of the cyclists' eye-gazing data in the multi-player blocks was lost due to the failure of eye-tracking.

Besides, all the participants also filled in the post-experiment questionnaire.

5.1.2. Data Processing

The pedestrians' speed profiles, derived from trajectory data, were smoothed using a one-dimensional Gaussian filter with a standard deviation of 12 for the Gaussian kernel. These refined profiles were then analyzed to identify the timestamp corresponding to the final crossing intention. As illustrated in Figure 5.1, two examples of the speed profiles demonstrate the data processing steps. To pinpoint the crossing intention point, all behavioral change points were first categorized into three types: lowest speed points, acceleration points, and deceleration points. The crossing intention point was defined as the final behavioral change point occurring before the pedestrian entered the area directly in front of the AV, as indicated by the green vertical line in Figure 5.1.

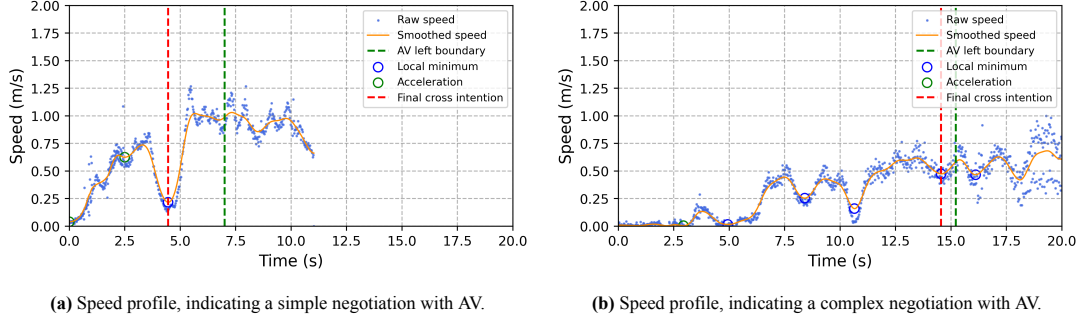


Figure 5.1: Speed profiles of the pedestrians.

5.1.3. Preliminary Analysis

One interesting observation from the trajectory dataset was that participants, acting as pedestrians in VR, tended to approach the center of the shared space during the crossing, as shown in Figure 5.2. However, this behavior varied depending on the presence of another road user, whether a pedestrian or a cyclist.

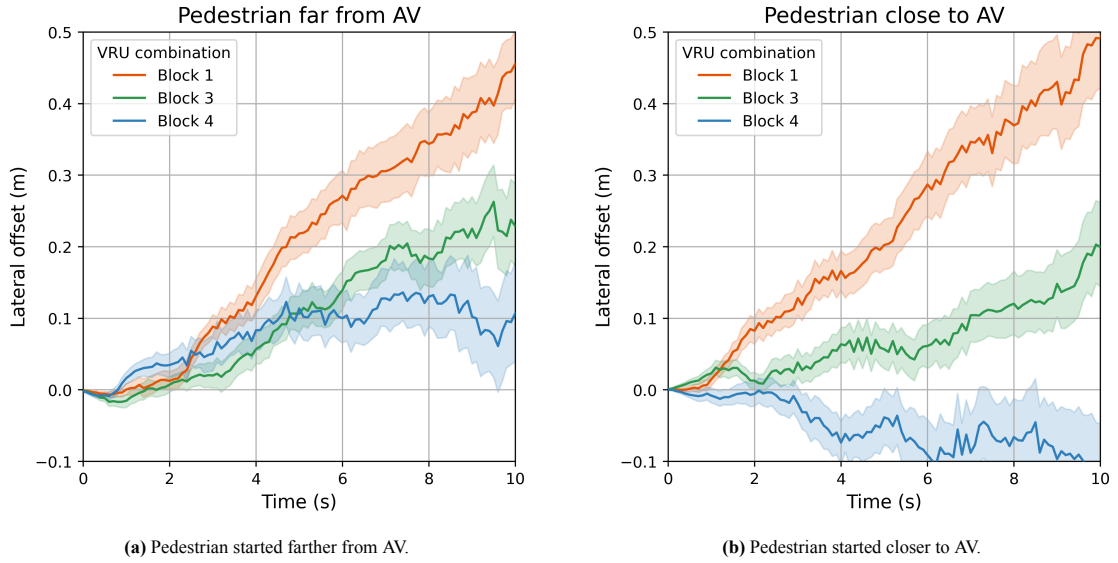


Figure 5.2: Lateral offsets of pedestrians from the origin during crossing. The shaded area represents the 95% confidence interval.

For single pedestrians (Block 1), participants consistently showed the largest lateral offset, both when close to and far from the AV. This indicated that pedestrians when crossing alone, tended to move toward the center of the shared space. In the dual pedestrian scenario (Block 3), the lateral offsets were somewhat smaller compared to the single pedestrian scenario. This suggested that when another pedestrian was crossing alongside, participants adjusted their strategy. The coordination between the two pedestrians likely led to less emphasis on moving toward the center of the road, resulting in smaller lateral offsets. In the pedestrian-cyclist mixed scenario (Block 4), the lateral offsets showed notable differences, likely due to the contrasting interactions between pedestrians and cyclists. When the pedestrian began near the AV, the negative lateral offset suggested that the cyclist exerted

a repulsive force on the pedestrian. Conversely, when the pedestrian started further from the AV, the offset tended to be positive, indicating that the pedestrian was more inclined to move toward the center of the shared space.

In conclusion, the offset data showed that pedestrians' behavior was affected by the presence of other road users. When crossing alone, pedestrians tended to move closer to the center of the road in the shared space. When crossing with another pedestrian, they made fewer adjustments to their path. However, when a cyclist was present, the pedestrian's behavior varied depending on their relative position, with both repulsive and attractive effects observed.

5.2. Objective Measures

Six distinct objective measures were derived from the datasets, and Linear Mixed Models (LMMs) were employed to examine these six objective measures to analyze the behavior of VRUs and their interaction with the AV in shared space.

5.2.1. Negotiation Time

The LMM analysis for negotiation time is provided in Table 5.2. The distributions of negotiation time for pedestrians and cyclists are illustrated in Figure 5.3, via a combination of violin and strip plots.

Table 5.2: Summary of the LMM analysis for the negotiation time of the pedestrian and cyclist.

Pedestrian				Cyclist			
Fixed effects	Est.	SE	p-value	Fixed effects	Est.	SE	p-value
β_0	8.192	0.452	<0.001	β_0	2.068	0.258	<0.001
$\mu_{Block:ped} \oplus ped$	-1.643	0.524	0.002	$\mu_{Block:ped} \oplus cyc$	0.077	0.295	0.794
$\mu_{Block:ped} \oplus cyc$	-2.809	0.528	<0.001	$\mu_{Loc:close}$	0.001	0.277	0.998
$\mu_{Loc:close}$	-2.233	0.520	<0.001	$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	-0.044	0.396	0.912
$\mu_{Block:ped} \oplus ped \times \mu_{Loc:close}$	2.340	0.740	0.002				
$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	2.864	0.743	<0.001				
Random effects	Var	SD	p-value	Random effects	Var	SD	p-value
$\psi_{pair} : \psi_{player}$	0.607	0.779	0.117	$\psi_{pair} : \psi_{player}$	0.679	0.824	0.005
ψ_{pair}	1.077	1.038	0.058	ψ_{pair}	0.222	0.471	0.474
Residual	5.407	2.325		Residual	1.537	1.240	
Model				Model			
Observations	235			Observations	157		
Marginal R^2	0.0996			Marginal R^2	0.0004		
Conditional R^2	0.3134			Conditional R^2	0.3698		
logLik	-550.6			logLik	-278.9		
AIC	1119.3			AIC	571.7		
BIC	1150.4			BIC	593.1		

The LMM analysis revealed significant fixed effects on pedestrians' negotiation time across different VRU combinations and initial relative locations to AV. The intercept was 8.192 seconds, representing the average negotiation time for a single pedestrian starting from a farther location relative to the AV. VRU crossing in pairs significantly influenced pedestrians' negotiation time. In scenarios involving two pedestrians crossing together, the negotiation time was reduced by 1.643 seconds compared to the single-pedestrian scenario. When the VRU combination included a pedestrian-cyclist pair, the pedestrian's negotiation time further decreased by 2.809 seconds. The initial location also played a significant role. Starting closer to the AV significantly reduced the negotiation time by 2.233 seconds. Interaction terms revealed a moderating effect of the initial location on VRU combinations: For dual-pedestrian scenarios, the reduction in negotiation time associated with starting closer to the AV was moderated, resulting in a slight increase in negotiation time. Similarly, in pedestrian-cyclist pairs, starting closer to the AV moderated the reduction in negotiation time with another slight increase.

In contrast, the LMM for cyclists showed a lower baseline negotiation time with an intercept of 2.068 seconds. However, none of the fixed effects, including VRU combinations or initial locations, were statistically significant. This suggests that cyclists' negotiation time remained relatively stable under all experimental conditions.

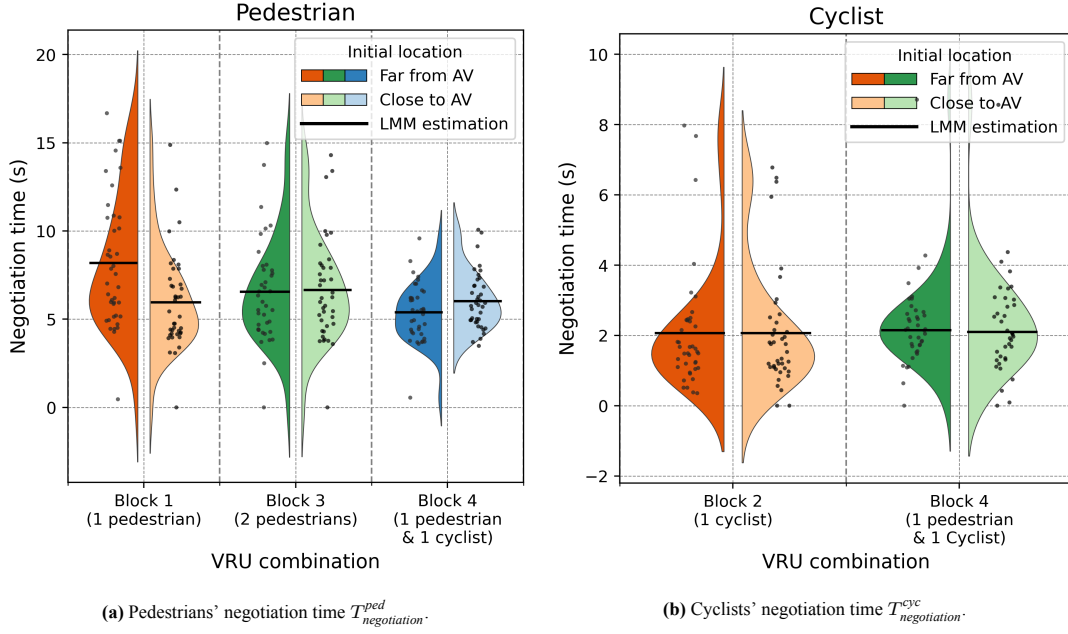


Figure 5.3: The violin and strip plots of pedestrians and cyclists negotiation time $T_{negotiation}$.

For pedestrians, the LMM analysis not only confirms the previous studies [17, 16, 29], which demonstrate that a pedestrian's movement dynamics can be influenced by neighboring pedestrians when crossing as part of a group but also extend this understanding to mixed groups of pedestrians and cyclists, yielding similar results. In contrast, cyclists' behaviors were largely unaffected, aside from slight adjustments in space gaps. This indicates that cyclists are less likely to exhibit behavioral changes when crossing as part of a group. We interpret this as indicating that pedestrians and cyclists may perceive the presence of other VRUs differently in terms of group association. For instance, [103] found that cyclists often adjust their paths to 'weave around' pedestrians, emphasizing their preference for independence. Similarly, [75] observed that pedestrians and cyclists tend to naturally segregate when traveling in the same direction within shared lanes.

While most findings in our study align with previous research [16, 29], some observed collective behaviors differed in [17]. Notably, we found that the negotiation time for the pedestrian farther from the AV decreased significantly when crossing with another VRU, contrasting with the increment in [17]. This quicker decision-making aligns more closely with real-world observations [29] and other VR experiments involving full-body-represented pedestrians [36]. The explanation provided in [17]—that pedestrians were distracted—may stem from the limited body representation (head and shoulders only) used in that study, unlike the full-body representation in ours. Furthermore, the similar negotiation times observed between paired VRUs in our study suggest that collective behavior fosters a synchronized crossing pattern, consistent with findings in [18].

5.2.2. Crossing Time

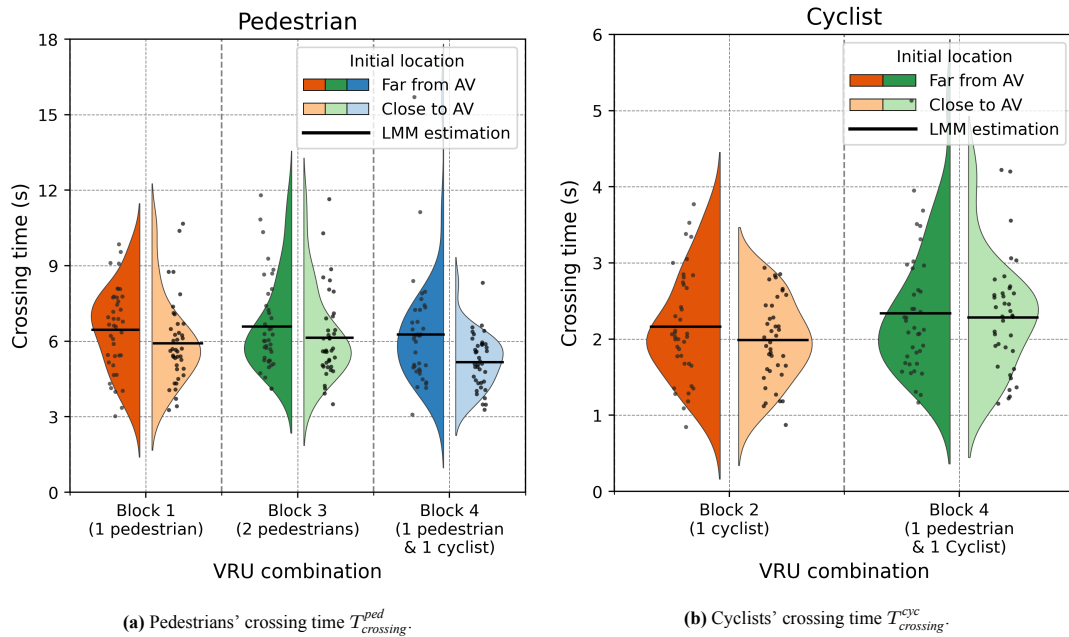
Table 5.3 presents the LMM analysis of crossing time for pedestrians and cyclists, respectively. The distributions of their crossing times are visualized in Figure 5.4.

The LMM result reveals that both the number and role of the VRU, as well as the initial relative location to the AV, do not have a statistically significant influence on the crossing time for pedestrians and cyclists. This indicates that the crossing behavior, in terms of the time to cross, remains consistent irrespective of the number of VRUs or their initial positions relative to the AV.

Our findings align with the results of the previous study [17], which examined two pedestrians crossing together in a shared space. This consistency suggests that the primary interaction between VRUs and the AV occurs during the negotiation phase, rather than the crossing phase. Moreover, it verifies that cyclists, as another category of VRUs, demonstrate a similarly consistent behavior when interacting with the AV during the crossing phase.

Table 5.3: Summary of the LMM analysis for the crossing time of the pedestrian and cyclist.

Pedestrian				Cyclist			
Fixed effects	Est.	SE	p-value	Fixed effects	Est.	SE	p-value
β_0	6.456	0.281	<0.001	β_0	2.162	0.114	<0.001
$\mu_{Block:ped} \oplus ped$	0.121	0.342	0.725	$\mu_{Block:ped} \oplus cyc$	0.176	0.153	0.252
$\mu_{Block:ped} \oplus cyc$	-0.192	0.345	0.578	$\mu_{Loc:close}$	-0.176	0.150	0.245
$\mu_{Loc:close}$	-0.546	0.340	0.110	$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	0.123	0.215	0.569
$\mu_{Block:ped} \oplus ped \times \mu_{Loc:close}$	0.101	0.484	0.835				
$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	-0.547	0.485	0.261				
Random effects	Var	SD	p-value	Random effects	Var	SD	p-value
$\psi_{pair} : \psi_{player}$	0.285	0.534	0.073	$\psi_{pair} : \psi_{player}$	0.021	0.145	0.649
ψ_{pair}	0.277	0.527	0.182	ψ_{pair}	0.025	0.158	0.549
Residual	2.309	1.520		Residual	0.451	0.672	
Model				Model			
Observations	235			Observations	157		
Marginal R^2	0.0693			Marginal R^2	0.0358		
Conditional R^2	0.2516			Conditional R^2	0.1245		
logLik	-448.7			logLik	-166.6		
AIC	915.3			AIC	347.2		
BIC	946.5			BIC	368.6		

**Figure 5.4:** The violin and strip plots of pedestrians and cyclists crossing time $T_{crossing}$.

5.2.3. Space Gap

The LMM analysis of the space gap is summarized in Table 5.4. Figure 5.5 presents the corresponding space gap distributions for pedestrians and cyclists, respectively.

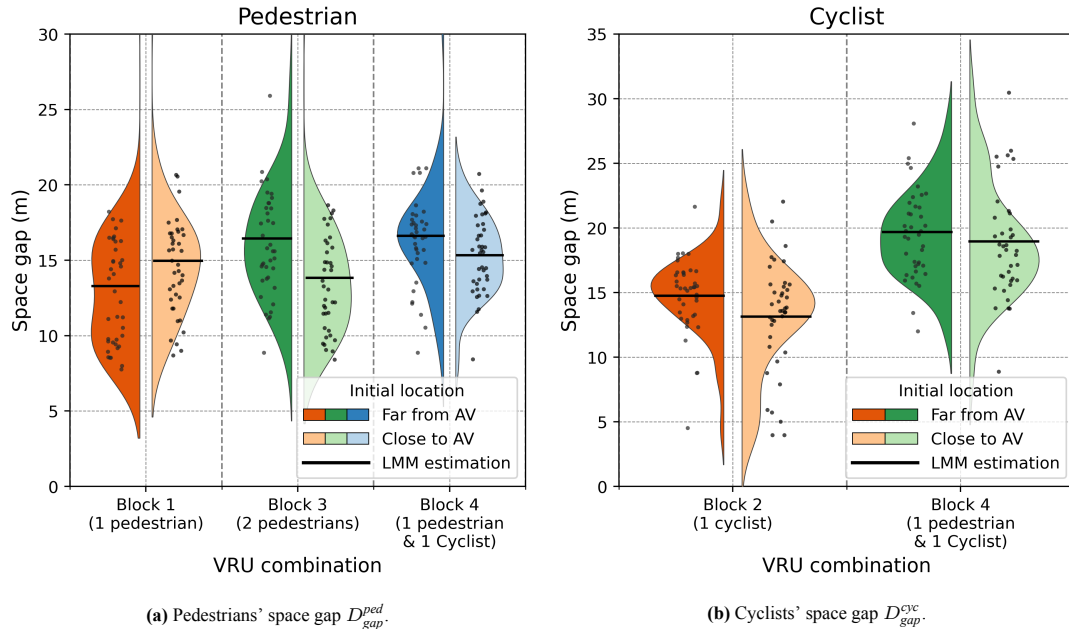
For pedestrians, the baseline scenario, in which a single pedestrian started far from the AV, estimated the space gap at 13.297 meters, representing the average distance at which a pedestrian initiated a crossing decision. In more complex scenarios, such as dual-pedestrian or pedestrian-cyclist pairs, the space gap increased significantly by 3.152 meters and 3.323 meters, respectively. Proximity to the AV is another critical factor in pedestrians' decision-making process. When a pedestrian started closer to the AV, the space gap increased by 1.663 meters, indicating greater caution close to the AV. However, the interaction between the VRU combination and the initial

Table 5.4: Summary of the LMM analysis for the space gap of the pedestrian and cyclist.

Pedestrian				Cyclist			
Fixed effects	Est.	SE	p-value	Fixed effects	Est.	SE	p-value
β_0	13.297	0.694	<0.001	β_0	14.748	0.620	<0.001
$\mu_{Block:ped} \oplus ped$	3.152	0.838	<0.001	$\mu_{Block:ped} \oplus cyc$	4.945	0.735	<0.001
$\mu_{Block:ped} \oplus cyc$	3.323	0.844	<0.001	$\mu_{Loc:close}$	-1.599	0.700	0.0242
$\mu_{Loc:close}$	1.663	0.832	0.047	$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	0.866	0.999	0.389
$\mu_{Block:ped} \oplus ped \times \mu_{Loc:close}$	-4.286	1.185	<0.001				
$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	-2.958	1.189	0.014				
Random effects	Var	SD	p-value	Random effects	Var	SD	p-value
$\psi_{pair} : \psi_{player}$	0.229	0.478	0.784	$\psi_{pair} : \psi_{player}$	0.679	0.824	0.043
ψ_{pair}	2.587	1.609	0.018	ψ_{pair}	0.222	0.471	0.363
Residual	13.856	3.722		Residual	1.537	1.240	
Model				Model			
Observations	235			Observations	157		
Marginal R^2	0.083			Marginal R^2	0.0004		
Conditional R^2	0.238			Conditional R^2	0.3698		
logLik	-655.2			logLik	-278.9		
AIC	1328.3			AIC	571.7		
BIC	1359.4			BIC	593.1		

location shows more nuanced results. Specifically, in dual-pedestrian and pedestrian-cyclist scenarios, starting closer to the AV resulted in a reduction of the space gap of 4.286 meters for dual pedestrians and 2.958 meters for pedestrian-cyclist pairs.

For cyclists, the baseline scenario, where a single cyclist started far from the AV, estimated the space gap at 14.75 meters, reflecting the distance at which cyclists typically signaled their crossing intention. In pedestrian-cyclist pair scenarios, the space gap increased significantly by 4.94 meters, suggesting that the presence of an additional VRU elevated interaction complexity, prompting earlier crossing decisions. In contrast, starting closer to the AV reduced the space gap by 1.60 meters.

**Figure 5.5:** The violin and strip plots of pedestrians and cyclists' space gap D_{gap} .

These findings suggest that the presence of another VRU may lead both pedestrians and cyclists to initiate their

crossing decision earlier. The presence of multiple VRUs likely encourages VRUs to exhibit the crossing intention earlier, thus reducing the time to negotiate and wait. This pattern of earlier crossing behavior is also reflected in the corresponding negotiation time data shown in Table 5.2.

5.2.4. Average Speed

Table 5.5 provides a summary of the LMM analysis of average speeds for both pedestrians and cyclists. The distributions of average speeds for both pedestrians and cyclists are illustrated in Figure 5.6.

Table 5.5: Summary of the LMM analysis for the average speed of the pedestrian and cyclist.

Pedestrian				Cyclist			
Fixed effects	Est.	SE	p-value	Fixed effects	Est.	SE	p-value
β_0	0.612	0.025	<0.001	β_0	2.217	0.128	<0.001
$\mu_{Block:ped} \oplus ped$	0.041	0.021	0.055	$\mu_{Block:ped} \oplus cyc$	-0.180	0.151	0.234
$\mu_{Block:ped} \oplus cyc$	0.100	0.021	<0.001	$\mu_{Loc:close}$	0.102	0.142	0.476
$\mu_{Loc:close}$	0.107	0.021	<0.001	$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	-0.096	0.203	0.635
$\mu_{Block:ped} \oplus ped \times \mu_{Loc:close}$	-0.085	0.030	0.005				
$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	-0.086	0.030	0.005				
Random effects	Var	SD	p-value	Random effects	Var	SD	p-value
$\psi_{pair} : \psi_{player}$	0.004	0.066	<0.001	$\psi_{pair} : \psi_{player}$	0.166	0.407	0.015
ψ_{pair}	0.006	0.075	0.019	ψ_{pair}	0.042	0.204	0.551
Residual	0.009	0.094		Residual	0.402	0.634	
Model				Model			
Observations	235			Observations	157		
Marginal R^2	0.0873			Marginal R^2	0.0232		
Conditional R^2	0.5713			Conditional R^2	0.3556		
logLik	183.7			logLik	-172.1		
AIC	-349.4			AIC	358.2		
BIC	-318.3			BIC	379.6		

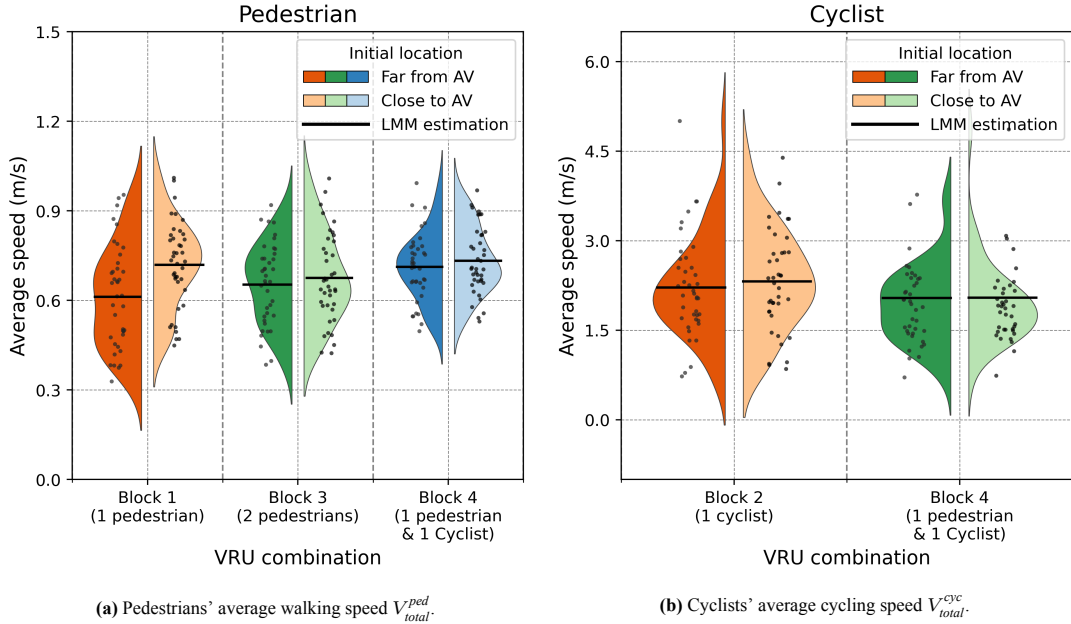


Figure 5.6: The violin and strip plots of pedestrians and cyclists' average speed V_{total} .

Pedestrian behavior exhibited notable patterns in average walking speeds. The baseline speed of approximately 0.612 m/s was statistically significant. Interestingly, the co-existence of another VRU led to a higher average

walking speed for pedestrians. While the presence of another pedestrian did not substantially alter this speed (0.041 m/s), encountering a cyclist leads to a marked increase of 0.100 m/s.

The initial position of pedestrians also proved influential, with those starting close to the AV demonstrating significantly higher speeds compared to their opposite-side counterparts. However, the initial location appeared to be moderated in certain VRU combinations, as evidenced by significant interaction effects. When paired with either another pedestrian or a cyclist, and starting close to the AV, pedestrians showed a slight decrease in speed, with estimates of -0.085 and -0.086, respectively.

In contrast, cyclists maintained a higher baseline average speed of 2.217 m/s, which was also statistically significant. However, their speeds remained largely unaffected by VRU combinations or starting positions. Unlike pedestrians, cyclists did not exhibit significant variations in speed across different conditions, including interactions with other VRUs or variations in their initial location. This consistency in cycling speed reflected a more uniform approach to crossing behavior among cyclists compared to pedestrians.

Compared to the literature [17, 19], which shows a decrease in the average crossing speed of two pedestrians as a pair, our results indicate that the speeds of two pedestrians converge to a similar level, with the pedestrian further away increasing their speed and the pedestrian closer decreasing theirs. This convergence was also observed when accompanied by a cyclist.

There are two possible explanations: Firstly, the familiarization of participants with VR may lead to a particularly low speed for the single pedestrian at the farther position, making it inconsistent with the literature. Secondly, pedestrians starting at a farther location may not feel as pressed by the AV and adopt a relatively relaxed walking style. However, the presence of another VRU may encourage the participant to consider social information and cross as a group.

5.2.5. Total Distance

Table 5.6 provides a summary of the LMM results for pedestrians' total walking distance. Figure 5.7 illustrates the total walking distance of pedestrians across various VRU combinations and starting locations.

Table 5.6: Summary of the LMM analysis for the pedestrians' total walking distance.

Fixed effects	<i>Est.</i>	<i>SE</i>	<i>p-value</i>
β_0	8.238	0.057	<0.001
$\mu_{Block:ped} \oplus ped$	-0.078	0.063	0.213
$\mu_{Block:ped} \oplus cyc$	-0.171	0.063	0.008
$\mu_{Loc:close}$	-0.118	0.062	0.059
$\mu_{Block:ped} \oplus ped \times \mu_{Loc:close}$	0.123	0.089	0.165
$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	0.062	0.089	0.486
Random effects	<i>Var</i>	<i>SD</i>	<i>p-value</i>
$\psi_{pair} : \psi_{player}$	0.034	0.186	<0.001
ψ_{pair}	0.009	0.094	0.485
Residual	0.077	0.278	
Model			
Observations	235		
Marginal R^2	0.042		
Conditional R^2	0.386		
logLik	-61.6		
AIC	141.3		
BIC	172.4		

Based on the analysis, the intercept is 8.238 meters and is highly significant, representing the baseline walking distance when all other factors are at their reference levels. A significant effect of pedestrian-cyclist joint crossing indicates that pedestrians walked less distance in Block 4 compared to the reference level. The effect of double-pedestrian crossing and the closer location are not statistically significant at the 0.05 level, although the closer location shows a trend towards significance. The interactions between VRU combinations and locations are also not significant, suggesting that the effect of locations does not significantly vary across blocks.

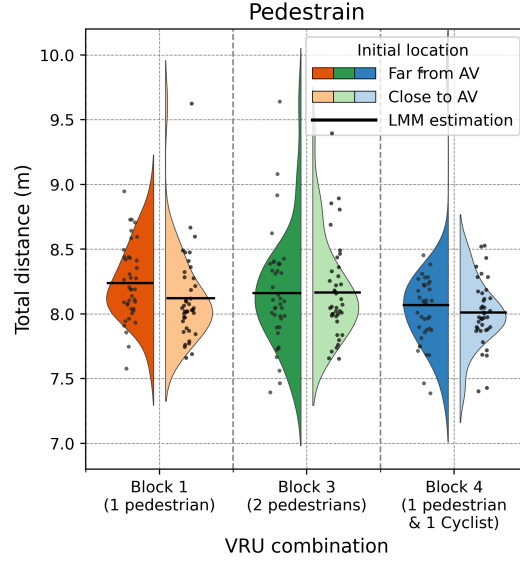


Figure 5.7: The violin and strip plots of the pedestrians' total walking distance D_{total}^{ped} .

Although the effect of an accompanying pedestrian on the total walking distance was not significant in our study, a decrease was observed. A similar significant trend was reported in [17], supporting the explanation that two pedestrians follow the shortest path when crossing the road. Additionally, we extend this explanation to cyclists, demonstrating that their presence exerts a greater regulatory effect on pedestrian walking direction, as shown in Figure 5.2.

5.2.6. AV-Gazing Time

Table 5.7 and Figure 5.8 summarize the LMM results for pedestrians' AV-gazing time, revealing significant fixed effects, particularly related to the number and role of VRU.

Table 5.7: Summary of the LMM analysis for the pedestrians' AV-gazing time.

Fixed effects	Est.	SE	p-value
β_0	2.607	0.247	<0.001
$\mu_{Block:ped} \oplus ped$	-1.081	0.270	<0.001
$\mu_{Block:ped} \oplus cyc$	-1.234	0.275	<0.001
$\mu_{Loc:close}$	-0.468	0.256	0.070
$\mu_{Block:ped} \oplus ped \times \mu_{Loc:close}$	0.611	0.371	0.101
$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	0.236	0.373	0.528
Random effects	Var	SD	p-value
$\psi_{pair} : \psi_{player}$	1.024	1.012	<0.001
ψ_{pair}	0.000	0.000	1.000
Residual	1.032	1.016	
Model			
Observations	179		
Marginal R^2	0.1076		
Conditional R^2	0.5521		
logLik	-289.4		
AIC	596.7		
BIC	625.4		

The baseline scenario, where pedestrians started at the farther location in the absence of the second VRU, showed an estimated AV-gaze time of 2.607 seconds. The analysis highlighted a significant reduction in AV-gaze time when pedestrians were accompanied by a second pedestrian or cyclist, with reductions of 1.081 seconds and

1.234 seconds, respectively. The effect of proximity to the AV was not significant, with the estimated change in gaze time being -0.468 seconds for pedestrians starting closer to the AV, though this effect was only marginally significant ($p = 0.070$). Interaction effects between the VRU combination and initial location were also non-significant.

Our findings indicate that when a pedestrian is accompanied by another VRU, their AV-gazing time decreases compared to when crossing alone, aligning with the results of [19], where two pedestrians encountered an HDV. In another study focusing on AV in shared space [17], the pedestrian further from the AV showed a significant decrease in AV-gazing time compared to crossing alone, but the pedestrian closer to the AV exhibited an insignificant slight increase. Our study similarly reveals that the closer pedestrian's AV-gazing time decreases less than that of the further pedestrian. This further confirms that group dynamics may cause the pedestrian farther from the AV to spend less time focusing on it, however, the AV-gazing time changes of the pedestrian closer to the AV does not reach an agreement. We assume this inconsistency is caused by the body representation used in [17], which distracts the pedestrian's focus and only the partial body representation may not fully exhibit the social communication, hence the participant further needs more time to interpret the interaction. What's more, our study found that pedestrians closer to AV decrease their AV-gazing time when a cyclist crosses. This may also indicate that the existence of cyclists also distracts the pedestrian's original focus on AV, making the interaction a little bit complex.

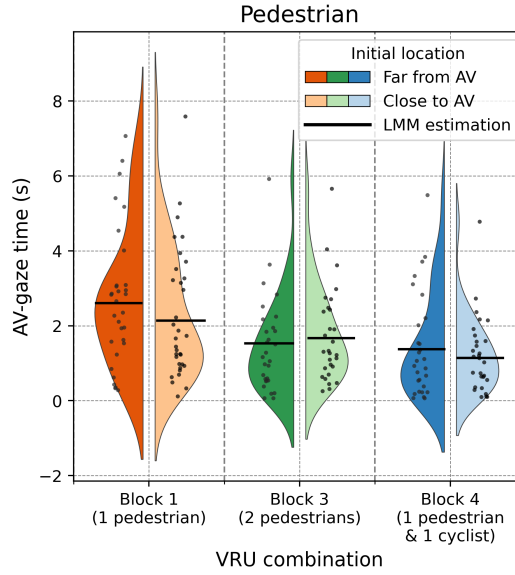


Figure 5.8: The violin and strip plots of the pedestrian AV-gazing time T_{AV}^{ped} .

Overall, our AV-gazing LMM analysis not only confirms the previous findings on the impact of another VRU accompanying a pedestrian on decreasing the pedestrians' AV-gazing time but also emphasizes the distraction effect of another cyclist on the pedestrian closer to the AV. A limitation of the current study is that it only analyzed AV-gazing data, without including gazing data on other road users during the experiment. Future research should conduct a more comprehensive eye-tracking study to examine eye-gazing distribution across various objects and road users during the crossing.

5.3. Subjective Measures

This section analyzes subjective measures, beginning with four metrics related to the simulator assessment, followed by two crossing-related subjective metrics, and concluding with participants' feedback on the co-simulator.

5.3.1. Simulator Sickness

The average overall score of the Simulator Sickness Questionnaire (SSQ) is 36.18 ± 36.53 , which is slightly higher than [17]. The result in Table 5.8 presents the average scores for three sub-scales of SSQ, namely nausea, oculomotor, and disorientation. Among the sub-scales, disorientation received the highest average score of 45.24 ± 54.39 , indicating that participants experienced disorientation symptoms most intensely. This was followed

by oculomotor symptoms, with a mean score of 32.97 ± 28.80 , suggesting moderate effects on visual and eye-related comfort. Nausea received the lowest average score of 19.79 ± 24.48 , showing relatively fewer symptoms related to stomach discomfort. These scores highlighted that disorientation was the most prominent symptom experienced, whereas nausea was less common among participants.

Table 5.8: The average scores of the sub-scales of SSQ.

Sub-scale	SSQ score (Mean \pm Std)
Nausea	19.79 ± 24.48
Oculomotor	32.97 ± 28.80
Disorientation	45.24 ± 54.39

In terms of motion sickness, the pedestrian VR simulator was promising, as participants reported minimal motion sickness caused by it and none withdrew from the pedestrians' experiment, highlighting the system's comfort. The high acceptance of the simulator can be attributed to its implementation of free locomotion, which allowed participants to navigate freely within the room [95].

However, some participants reported slight and obvious motion sickness during cycling in VR. They suggested several enhancements to improve their VR cycling experience and to reduce the likelihood of sickness. They recommended incorporating steering functionalities to offer more control over movement and increase immersion, which aligns with similar research [71, 72]. Additionally, they suggested enhancing locomotion feedback, particularly in terms of acceleration and braking sensations, to help alleviate the sensory mismatch that can contribute to simulator sickness [72].

5.3.2. Realism

Table 5.9: The scores of realism questionnaire.

Items in the face validity questionnaire	Score (Mean \pm Std)
The realism of the virtual environment	3.78 ± 0.58
The realism of the virtual objects (e.g., AV)	3.75 ± 0.84
The realism of the movement ability as a pedestrian	3.55 ± 0.96
The realism of the movement ability as a cyclist	3.45 ± 0.99
The realism of the environmental sound	3.58 ± 1.06

The results in Table 5.9 reveal variations in perceived realism across different aspects of the virtual environment in the VR realism questionnaire. Overall, the realism of the virtual environment and virtual objects (e.g., AV) received relatively higher scores, with mean ratings of 3.78 ± 0.58 and 3.75 ± 0.84 , respectively. This suggests that participants found these visual elements particularly convincing within the VR scenarios.

In contrast, the realism scores for movement abilities as a pedestrian and as a cyclist were slightly lower, with means of 3.55 ± 0.96 and 3.45 ± 0.99 , indicating room for improvement in the naturalism of movement simulation, especially in terms of walking and cycling motions. Additionally, the environmental sound realism received a score of 3.58 ± 1.06 , slightly higher than the movement scores, indicating that sound contributed positively to immersion but still has potential for enhancement. The items with lower realism scores aligned with participant feedback and suggestions provided in Section 5.3.7.

The average score for the questionnaire was 3.62 ± 0.58 , aligning with scores from previous studies [99, 17] investigating pedestrian road-crossing behavior in VR. These scores indicate that the VR environment effectively provided a realistic experience for participants. However, there is scope for further optimization in motion simulation and auditory effects to enhance the overall realism of the experiment.

5.3.3. Presence

The presence questionnaire (PQ) results, shown in Table 5.10, highlight the performance of our virtual reality setup compared to the benchmark, which held a double-pedestrian crossing VR experiment in a shared space, where only the heads and shoulders of the pedestrians were displayed.

The results demonstrate that our VR setup performed well. For *Involvement*, our participants averaged a score of 4.919, slightly surpassing the benchmark's score of 4.77, suggesting our design was effective in engaging users.

Table 5.10: Comparison of average PQ sub-scale scores.

Sub-scale	Score (Mean \pm Std)	
	Ours	Benchmark
Involvement	4.919 \pm 0.965	4.77 \pm 0.81
Sensory fidelity	4.329 \pm 1.377	3.80 \pm 0.83
Immersion	5.522 \pm 0.780	5.38 \pm 0.76
Interface quality [†]	3.217 \pm 1.658	3.96 \pm 1.10

[†] Reversed items.

On *Sensory fidelity*, our VR co-simulator scored 4.329, significantly outperforming the benchmark's 3.80, indicating a more realistic sensory experience in our VR setup. Regarding *Immersion*, our score of 5.522 was marginally higher than the benchmark's 5.38, showing that our environment provided a slightly more immersive experience. For *Interface quality*, a collection of reversed items, our score of 3.217 was lower than the benchmark's 3.96, meaning our interface was rated as more user-friendly and efficient.

Overall, the PQ results indicate that the VR experiment using our developed VR co-simulator offers a more effective and engaging VR experience than the previous study, especially in terms of sensory fidelity and interface quality. This can be attributed to the co-simulator's efforts to establish interactions between VRUs and AVs. Specifically, the introduction of various transport modes (i.e., pedestrian and cyclist) and the inclusion of participants' real-time behaviors in the same virtual world may have made participants feel more immersed and reactive in VR compared to earlier implementations [17].

5.3.4. System Usability

Table 5.11 presents the System Usability Scale (SUS) scores for the two VR body tracking sub-systems used in the VR experiment. The pedestrian full-body tracking subsystem received a mean SUS score of 47.94 with a standard deviation of 14.24, while the cyclist upper-body tracking subsystem had a mean score of 46.50 with a standard deviation of 13.56. According to the SUS scale, scores range from 0 to 100, with higher scores indicating greater usability. A score of 80.3 or higher is considered excellent, suggesting that users find the system highly usable and will likely recommend it to others. Scores around 68 indicate average usability, where the system performs adequately but has some areas where the user experience could be enhanced. A score of 51 or below signals a failing grade, highlighting significant usability challenges that require immediate attention to improve the system's effectiveness and user satisfaction.

Table 5.11: The average SUS scores for two body-tracking sub-systems.
The SUS score ranges from 0 to 100, with higher scores indicating better usability.

Subsystem	SUS score (Mean \pm Std)
Pedestrian full-body tracking	47.94 \pm 14.24
Cyclist upper-body tracking	46.50 \pm 13.56

If readers are interested in the specific scores of the SUS, please refer to the appendix for detailed scores for each item. Tables B.1 and B.2 provide the scores for each item in the SUS questionnaire, offering insights into the usability assessment of both the pedestrian full-body tracking and cyclist upper-body tracking systems.

Regarding usability, the VR experiment's evaluation of body tracking systems for pedestrians and cyclists yielded results approaching an acceptable standard. Although participant feedback highlighted lower levels of satisfaction, indicating areas for potential improvement, it is crucial to acknowledge that these systems are still in the prototype stage. Despite their early development phase, the systems showcased notable reliability and functionality during the VR trials. This highlights the feasibility of employing VR systems that enable real-time body tracking and realistic representation of pedestrians and cyclists, rather than relying on partial body representations [17] or simplistic geometric proxies [22, 18].

5.3.5. Trust in AV

The level of trust in AVs was measured per participant using a scale ranging from 1 to 7 [101, 13]. This scale contained questions such as “Globally, I trust the automated vehicle”, “I trust the automated vehicle to have seen

me”, and “I trust the automated vehicle to drive safely”. Table 5.12 presents the trust in AV scores, categorized by overall participants and further divided by gender.

Table 5.12: The average score of trust in AV.

Group	Sample size	Trust in AV (Mean \pm Std)
Overall	40	5.01 \pm 1.11
Male	20	4.65 \pm 1.22
Female	20	5.37 \pm 0.87

The mean score was 5.01 ± 1.11 , indicating a moderate level of trust in the AV, which is slightly higher than the previous study [17] (4.42 ± 1.09). Furthermore, the T-test ($t = -2.13, p = 0.04, df = 34.4$) and Mann-Whitney U test ($U = 127.5, p = 0.049$) were conducted to evaluate gender-based differences in trust in the AV. The results indicate a statistically significant difference in trust levels between genders, with males showing slightly lower trust in the AV compared to females.

5.3.6. Perceived Behavioral Control and Risk

Table 5.13 shows the average scores of both the perceived behavioral control (PBC) and perceived risk (PR) questionnaires, categorized by overall participants as well as by gender.

Table 5.13: The average scores of PBC and PR.

Group	Sample size	PBC (Mean \pm Std)	PR (Mean \pm Std)
Overall	40	2.41 \pm 1.14	5.56 \pm 1.07
Male	20	2.72 \pm 1.43	5.35 \pm 1.14
Female	20	2.10 \pm 0.64	5.78 \pm 0.96

Perceived Behavioral Control

PBC refers to an individual’s belief about their ability to perform a particular behavior, according to the theory of planned behavior [104]. The PBC questionnaire comprised two items on a 7-point bipolar scale: “For me, crossing the road in this way would be ...” and “I believe I have the ability to cross the road in this way as described in this situation.” The first item was rated on a scale from very easy (score 1) to very difficult (score 7), while the second item was rated from strongly agree (score 1) to strongly disagree (score 7). It is important to note that we utilized an inverted 7-point scale for PBC measurement.

These two items together resulted in an average PBC score of 2.14 ± 1.14 , which is lower than the scores recorded for individual participants interacting with an AV (3.16 ± 1.63) or an HDV (3.28 ± 1.77) in the conventional street as per [13], and for two pedestrians crossing simultaneously with an AV in shared space (2.73 ± 0.96) according to [17]. It confirms that pedestrians show a greater intention to cross in shared spaces compared to conventional road environments. Additionally, this suggests that crossing with another VRU may boost the VRU’s confidence to cross when interacting with an AV. The analysis of PBC scores by gender further revealed observed differences between males and females, yet the T-test and Mann-Whitney U test results indicate these differences are not statistically significant, which aligns with the previous findings on the gender effect in [13].

Perceived Risk

Based on the version used in [17], the PR questionnaire has been updated to include three specific crossing scenarios as a pedestrian: (1) crossing the road alone, (2) crossing with another pedestrian, and (3) crossing with a cyclist. Respondents rated these items on a 7-point scale from very unsafe (score 1) to very safe (score 7).

The refined PR questionnaire resulted in an average score of 5.56 ± 1.07 , which is similar to [17] (5.09 ± 1.15). Specifically, PR scores were higher when crossing with another pedestrian (5.75 ± 1.08) or a cyclist (5.6 ± 1.06) compared to crossing alone as a pedestrian (5.35 ± 1.37). This suggests that crossing in pairs enhances the perceived safety of VRUs.

5.3.7. Participant Feedback

At the end of the questionnaire, participants had the option to provide feedback and suggestions for improving the designed VR co-simulator. Twelve out of forty participants provided valid suggestions, which will be considered

to enhance the design and interaction of future versions of the multi-player VR experiment. Several key areas for improvement are summarized as follows, with the number following each bold item indicating how many participants suggested improvements in that area:

- **Cyclist simulator** (3): Add steering functionality. Keeping the bike moving straight without steering options caused some participants to experience more noticeable motion sickness, which is consistent with the simulator design recommendations from previous study [71, 72], especially compared to pedestrian free locomotion movement experience [95].
- **Vehicle dynamics** (3): Make vehicle behavior more realistic and less predictable.
- **Sound** (4): Introduce additional vehicles' sounds in the VR environment, while ensuring participants can still clearly hear instructions from the researcher.
- **multi-player latency** (1): Minimize latency to provide a smoother VR experience.
- **Room size** (1): A larger space for movement is desired to navigate freely [95] and to enhance safety.

Participants were also asked if they would like to receive updates about the project and participate in future experiments. Encouragingly, 26 of them expressed interest in staying informed and joining future VR studies!

6

Discussion

In this chapter, Section 6.1 addresses the five sub-research questions, while Section 6.2 summarizes the main research question.

6.1. Answers to Sub-Research Questions

This section addresses the five sub-research questions.

6.1.1. Answer to SQ1 Simulator Integration

The first sub-research question related to **simulator integration** is formulated as follows:

How can various existing VR simulators (i.e., pedestrian, cyclist) be effectively linked and integrated into a unified multi-player multi-mode co-simulator?

In this study, we initially examine the feasibility of integrating various VR road user simulators into the same VR environment. To achieve this, we utilize two existing VR road user simulators: a pedestrian VR simulator and a cyclist VR simulator. By leveraging the Unreal Engine 5 game engine, these simulators can be combined into a unified virtual space using the engine's built-in multi-player gaming functionality. Specifically, we choose a listen server-client architecture, where one client acts as the server during the connection. This connection architecture is currently capable of managing situations involving two VR participants. The original functionalities of two VR simulators are fully integrated into the multi-player VR co-simulator. As a result, the current VR co-simulator supports four different game modes: (1) *single-pedestrian*, (2) *single-cyclist*, (3) *double-pedestrian*, and (4) *pedestrian-cyclist mixed*. We anticipate that the same architecture can integrate additional categories of VR road user simulators, such as driver and wheelchair simulators.

6.1.2. Answer to SQ2 Interaction Development

The second sub-research question regarding **interaction development** is formulated as follows:

What types of interactions between different road users should be simulated in VR to achieve a similar level of realism as in the real world?

Following the integration of simulators, attention turns to facilitating interactions among different participants, since the initial simulators were not designed for multi-player scenarios. Previous studies have only partially illustrated the pedestrians' bodies, focusing on heads and shoulders, or even simplifying them into geometric shapes for ease. We aim to enhance this interaction by enabling participants to observe others' behaviors through real-time body movements, simulating human-to-human interactions in real-world traffic settings. This is achieved by utilizing body tracking technology to monitor key body parts of pedestrians and cyclists, such as hands, feet, and waists. An inverse kinematic algorithm in Unreal Engine 5 is then used to predict pedestrians' full-body movements based on these key body part transformations. Building on the full-body tracking of pedestrians, the cyclists' upper body tracking is developed, and the lower body is blended with predefined animations. Additionally, the MetaHuman feature is used to create high-quality digital human representations of participants. As a result, pedestrians and cyclists are depicted as realistic digital humans in VR, with their body movements tracked

and replicated in real time.

6.1.3. Answer to SQ3 Data Collection

The third sub-research question about **data collection** is formulated as follows:

What kinds of data from different road users during a multi-player VR experiment should be collected?

The primary objective of developing this VR co-simulator is to enable multi-player VR experiments as a viable data collection method for transportation research. Multi-player VR experiments should collect diverse data from various road users. We gather several types of data, including trajectory, body-tracking, and eye-gazing data. While the utility of these datasets has been explored in single-participant studies, they cannot fully capture the interactions between multiple road users simultaneously. By increasing the number of road users and introducing different roles, the data collected through multi-player VR experiments should provide deeper insights into the behaviors of road users and their interactions with AVs. Furthermore, by combining the post-experiment questionnaire, both objective and subjective measures can be analyzed from multiplayer VR experiments, creating a comprehensive data collection system.

6.1.4. Answer to SQ4 Co-simulator Assessment

The sub-research question 4 is about the **VR co-simulator assessment**, and is formulated as follows:

How to assess the effectiveness of the built VR co-simulator by a multi-player VR experiment?

After implementing a VR co-simulator, it is important to test its effectiveness. Hence, a VR experiment was designed and conducted to assess the effectiveness and usability of the developed VR co-simulator. After the experiment, the participants were asked to fill in a questionnaire including several parts assessing the simulator sickness, realism, presence, and body-tracking usability within the VR experiment.

In terms of simulator sickness, participants rated simulator sickness similarly to the previous study, indicating that the overall experiment did not induce excessive motion sickness. However, participant feedback suggests that the bike VR simulator needs improvements in steering and acceleration/brake control. Our study received higher scores for presence and realism compared to [17], suggesting that the addition of more road users with high-quality, full-body representations and real-time tracking enhanced the immersive and realistic experience in VR. Regarding system usability for body-tracking of pedestrians and cyclists, the results were adequate, indicating user acceptance of the subsystem. However, there is significant room for improvement since the subsystem is still a prototype. Future research plans include implementing more advanced body-tracking algorithms to provide a more accurate and flexible representation of different road users.

Overall, the VR experiment was successful, and the results presented in Section 8 validated the effectiveness of the VR co-simulator. The features introduced into the VR co-simulator are promising to contribute to transportation research.

6.1.5. Answer to SQ5 VRU-AV Interaction

The last sub-research question 5 focusing on the **VRU-AV interaction**, is formulated as follows:

How do the number of VRUs, their role, and their initial relative location influence the VRUs' behaviors and their interactions with the AV in shared space?

The VR experiment is also aimed to investigate the effects of the number of VRUs, their role, and their initial relative location on the VRUs' behaviors and interactions with the AV in shared space. Both objective metrics (i.e., negotiation time, crossing time, space gap ...) and subjective measures (i.e., trust in AV, perceived behavioral control ...) are examined to analyze the impact of VRU combinations and initial relative location.

In terms of the number and role of VRUs, the results indicate that both of them significantly influence pedestrians' negotiation time, total walking distance, AV-gazing time, and the space gap for both pedestrians and cyclists. For pedestrians, these findings are consistent with previous studies [17, 19, 29], which demonstrate that a pedestrian's movement dynamics can be influenced by neighboring pedestrians when crossing as part of a group. This understanding is extended to mixed groups of pedestrians and cyclists by our study, showing similar results. In contrast, cyclists' behaviors remained largely unchanged, except for slight adjustments in space gaps, indicating that cyclists are less likely to exhibit behavioral changes when crossing as part of a group. We interpret this as

suggesting that pedestrians and cyclists may perceive the presence of other VRUs differently in terms of group association.

Regarding the impact of the relative locations of the two VRUs, it had a significant impact on pedestrians' negotiation time and space gap. The interaction effects between the relative location and VRU combination are also significant. Our study observed more cooperative crossing behaviors of VRUs, compared to the previous conclusion that when crossing the road next to each other, two pedestrians could behave differently depending on their relative standing positions [17].

Besides objective metrics, subjective measures also reveal insights into the effect of VRUs' count and role. The result reports a higher trust in AV. Additionally, participants reported greater confidence in crossing the shared space with another VRU, whether pedestrian or cyclist, than when crossing alone. The subjective self-report is consistent with the objective metrics derived from the participants' behaviors.

Overall, we confirm the influence of the number of VRUs, their role, and the initial relative location on VRU-AV interaction in shared space. The observed decrease in negotiation time and AV-gazing time when pedestrians cross together suggests that mutual awareness and implicit coordination within a pair play a crucial role in making the crossing decisions. These results further underscore the importance of considering both individual and collective dynamics in studies of shared spaces, as synchronized behaviors and reduced attention to AVs may indicate an increased sense of confidence or trust among group members when navigating complex traffic scenarios.

6.2. Answer to Main Research Question

The main research question of this master's thesis is

How can a multi-player multi-modal road user virtual reality co-simulator be developed and tested to study the behaviors and interactions between various vulnerable road users?

To address this question, the study was conducted in two stages:

Development of the VR Co-simulator: In the first stage, we created a multi-user, multi-modal VR co-simulator that integrates pedestrian and cyclist VR simulators to address key research gaps in VR experiments, such as the absence of human-to-human interactions and challenges with scalability. Utilizing technologies like body tracking and MetaHuman, the system enables real-time interactions and detailed data collection, including trajectories, body movements, and eye-gaze behaviors, providing a foundation for future multi-player VR experiment studies.

VR Experiment Using the Co-simulator: In the second stage, a VR experiment was conducted using this VR co-simulator to 1) to assess the effectiveness of the developed VR co-simulator, and 2) explore how different VRU combinations (e.g. number of VRUs and role of VRUs) and VRUs' initial relative locations, affect VRUs' behaviors and their interactions with AVs. Shared space was selected as the studied road traffic scenario as it encourages more natural interactions, without explicit traffic rules, supporting the experiment's aim to study the interactions between VRUs and AV. The experiment involved 20 participant pairs acting as pedestrians and cyclists, with both objective data (e.g. trajectory, eye-gaze behavior) and subjective data (e.g. questionnaire responses) collected. The results from the VR experiment validate the effectiveness of the multi-player, multi-modal road user VR co-simulator. Additionally, the study illustrates the influence of the number of VRUs, their roles, and their initial relative locations on VRU-AV interactions in a shared space.

7

Conclusion

This chapter concludes the thesis by summarizing the key findings in Section 7.1, examining existing limitations in Section 7.2, and suggesting potential directions for future research in Section 7.3.

7.1. Conclusion

To summarize, we successfully designed and implemented a multi-player, multi-modal VR co-simulator that incorporates both pedestrians and cyclists into the same VR space. This VR co-simulator aims to support multi-player VR experiments for comprehensive data collection in transportation research. It supports nightly features such as body tracking for pedestrians and cyclists, MetaHuman - a high-quality digital human representation, and comprehensive data collection technologies such as body tracking and eye gazing data. A subsequent VR experiment was conducted to examine the effectiveness of the developed VR co-simulator and investigate the interaction between VRU and AV in shared space. The assessment of the co-simulator effectively proved its capabilities and feasibility, in terms of simulator sickness, presence, realism, and usability. The VR experiment also confirms the effect of VRU combinations and VRUs' initial relative locations on the VRU-AV interaction in shared space.

7.2. Current Limitations

The co-simulator design exhibited several shortcomings and limitations during the experiment. First, the body tracking setup needs refinement to achieve more accurate participant tracking. Second, the bicycle VR simulator requires enhancements, particularly in steering control, to improve its fidelity.

The VR experiment procedure also has limitations that may influence the results. First, the lack of randomization within each block could introduce learning effects. Second, the AV consistently approached the VRUs from their right-hand side, limiting scenario variability. Introducing more randomization is necessary in future studies.

7.3. Future Work

Several promising research directions could enhance the VR co-simulator and broaden the scope of VRU-AV interaction studies.

Increase Participants: Studying more complex interactions involves increasing the number of participants within the same VR scenario. This allows for the analysis of richer social dynamics and cooperative or competitive behaviors among multiple users. Expanding participant numbers provides more realistic and diverse data, enhancing the understanding of group-based decision-making processes in shared virtual environments.

Include More Road Users: Incorporating additional types of road users, such as drivers or wheelchair users, can simulate more diverse and intricate traffic interactions. This extension makes VR environments more representative of real-world conditions, improving the ecological validity of experiments. Including these road users also enables researchers to examine how different user groups interact and influence each other's behaviors.

Extended Reality Technologies: Using augmented reality (AR) and mixed reality (MR) enhances the scope of

multi-player VR experiments by blending virtual and real-world elements. These technologies facilitate more dynamic and immersive data collection while allowing for more flexible and adaptive experimental setups. By leveraging AR and MR, researchers can explore complex human-environment interactions and evaluate the impact of varying contextual factors on user behavior.

We are still in the initial stages of developing this comprehensive VR co-simulator that integrates various road users. We will keep evolving this project, adding more interesting features based on the identified limitations and summarized future directions above, and eventually contributing to the transportation research community!

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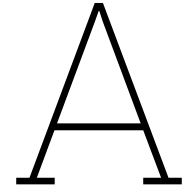
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Participant Demographic Information

Table A.1: Summary of Participant Demographics.

Descriptive information	Category	Number (%)
Gender	Male	20 (50.00%)
	Female	20 (50.00%)
Age group	10-19	0 (0.00%)
	20-29	34 (85.00%)
	30-39	5 (12.50%)
	40-49	0 (0.00%)
	50+	1 (2.50%)
Highest education level	High school or equivalent	2 (5.00%)
	Associate degree or equivalent	0 (0.00%)
	Bachelor's degree or equivalent	4 (10.00%)
	Master's degree or equivalent	29 (72.50%)
	Doctoral degree or equivalent	5 (12.50%)
Familiarity with any computer gaming	Never	3 (7.50%)
	Seldom	9 (22.50%)
	Sometimes	12 (30.00%)
	Often	8 (20.00%)
	Very often	8 (20.00%)
Previous experience with VR	Never	6 (15.00%)
	Seldom	15 (37.50%)
	Sometimes	12 (30.00%)
	Often	3 (7.50%)
	Very often	4 (10.00%)
Familiarity with the concept of shared space	Never	14 (35.00%)
	Seldom	8 (20.00%)
	Sometimes	2 (5.00%)
	Often	9 (22.50%)
	Very often	7 (17.50%)
Previous experience with shared space	Never	17 (42.50%)
	Seldom	4 (10.00%)
	Sometimes	8 (20.00%)
	Often	5 (12.50%)
	Very often	6 (15.00%)
Familiarity with the concept of automated vehicles	Never	3 (7.50%)
	Seldom	7 (17.50%)
	Sometimes	10 (25.00%)
	Often	11 (27.50%)
	Very often	9 (22.50%)
Previous experience with automated vehicles	Never	21 (52.50%)
	Seldom	8 (20.00%)
	Sometimes	6 (15.00%)
	Often	3 (7.50%)
	Very often	2 (5.00%)

B

SUS Questionnaire Item Scores

Table B.1: Results for each item in the SUS questionnaire of the pedestrian full-body tracking system.

Item	Score (Mean \pm SD)
I think that I would like to use this system frequently	3.51 \pm 0.61
I found the system unnecessarily complex.	2.61 \pm 0.79
I thought the system was easy to use.	3.60 \pm 0.72
I think that I would need the support of a technical person to be able to use this system.	3.00 \pm 0.87
I found the various functions in this system were well integrated.	3.63 \pm 0.55
I thought there was too much inconsistency in this system.	2.49 \pm 0.70
I would imagine that most people would learn to use this system very quickly.	3.47 \pm 0.84
I found the system very cumbersome to use.	2.59 \pm 0.74
I felt very confident using the system.	3.54 \pm 0.74
I needed to learn a lot of things before I could get going with this system.	2.48 \pm 0.79

Table B.2: Results for each item in the SUS questionnaire of the cyclist upper-body tracking system.

Item	Score (Mean \pm SD)
I think that I would like to use this system frequently	3.34 \pm 0.73
I found the system unnecessarily complex.	2.59 \pm 0.86
I thought the system was easy to use.	3.73 \pm 0.58
I think that I would need the support of a technical person to be able to use this system.	3.45 \pm 0.79
I found the various functions in this system were well integrated.	3.56 \pm 0.65
I thought there was too much inconsistency in this system.	2.52 \pm 0.76
I would imagine that most people would learn to use this system very quickly.	3.62 \pm 0.68
I found the system very cumbersome to use.	2.72 \pm 0.80
I felt very confident using the system.	3.52 \pm 0.65
I needed to learn a lot of things before I could get going with this system.	2.48 \pm 0.70

Studying the Interaction between Vulnerable Road Users and Automated Vehicle: A Pedestrian-Cyclist Virtual Reality Co-simulator and Experiment in Shared Space

Zhenlin (Gavin) Xu

Abstract—We have successfully designed and implemented a multi-player, multi-modal virtual reality (VR) co-simulator that integrates both pedestrians and cyclists within the same VR environment. This co-simulator is designed to support multi-player, multi-modal VR experiments aimed at comprehensive data collection in transportation research. It features advanced functionalities including body tracking for pedestrians and cyclists, high-quality digital human representations, and comprehensive data collection technologies such as eye gazing data. A VR experiment was conducted to evaluate the effectiveness of the VR co-simulator and investigate the interactions between vulnerable road users (VRUs) and automated vehicles (AVs) in shared spaces. The assessment demonstrated the co-simulator's capabilities and feasibility in terms of simulator sickness, presence, realism, and usability. The experiment also confirmed the impact of VRU combinations and initial relative positions on the interactions between VRUs and AVs in shared space.

Index Terms—Interaction, vulnerable road user, automated vehicle, virtual reality, co-simulator, shared space.

I. INTRODUCTION

Vulnerable Road Users (VRUs) refer to individuals on the road who lack the protection of an external shield, such as pedestrians and cyclists [1]. Due to their limited protection, VRUs usually face higher traffic risks than other road users [2]. Studying the VRUs' behaviors is necessary for enhancing road safety and reducing VRUs' injuries.

With recent advancements, Automated Vehicles (AVs) become promising to be deployed shortly. Compared to human-driven vehicles (HDVs), AVs will represent a new type of road user. This shift may pose potential risks for VRUs [3], who rely on not only explicit but also implicit communication, such as eye contact and gestures [4], with human drivers to negotiate. Therefore, investigating these potential VRU-AV interactions is essential to assess the safety, comfort, and acceptance of AVs by VRUs.

Traditionally, the road behaviors of VRUs are collected through various methods such as field observation [5], surveys [6]–[8], and video recording [9], [10]. Field observations and video recordings provide objective data on the natural behaviors and interactions of VRUs with vehicles, while surveys offer a straightforward means to assess road users' subjective experiences. However, since AVs are not yet officially deployed worldwide, these conventional data collection methods are inadequate for effectively studying VRU-AV interactions.

In recent years, Virtual Reality (VR) experiments have become a new data collection method, providing a safe and efficient way to study the VRUs' behaviors [11]. By creating immersive and interactive environments, VR allows participants to engage with traffic scenarios as if they were in real-world conditions. Additionally, VR can simulate hypothetical or futuristic scenarios, avoiding the potential safety and ethical issues associated with field experiments. These features make VR experiments particularly effective for studying interactions between VRUs and AVs [12], [13].

As interest in VR experiments to study VRU behaviors and interactions with AVs grows, several research gaps remain to be addressed. A majority of the current VR studies on VRU-AV interactions concentrate on isolated, single-participant scenarios, typically focusing on a single pedestrian [12] or a single cyclist interacting with vehicles [13] (either AVs or HDVs). While these studies provide valuable insights into individual behaviors, they fail to capture the collective behaviors within the VRU groups [14]. In real-world road situations, VRUs rarely cross the street alone. Only several studies [15]–[17] involving two pedestrians crossing the road together. Therefore, more efforts are needed to investigate how group dynamics influence VRU-AV interactions.

Furthermore, most existing VR studies do not account for multi-modal interactions. Multiple groups of road users introduce a higher complexity level compared to single-modal traffic scenarios. Overlooking these multi-modal interactions fails to represent realistic road behaviors accurately. Only a few studies focus on pedestrian-driver interactions [18], [19]. Hence, it is also essential to put in more effort to study the interactions between different groups of road users.

Additionally, in the limited literature involving multi-player and multi-modal interactions [15], [18], [19], the simulated interactions in VR remain too simple and incomplete. For example, pedestrians are often represented with only partial body representations [15] or merely with several geometric proxies [18], [19]. These representations may not be sufficient to capture human interactions' full complexity and realism, potentially introducing bias into the research findings. Thus, it's crucial to develop a more realistic VR co-simulator to enhance simulation fidelity and maintain realism.

The main research question of this study can be formulated as follows: *How can a multi-player multi-modal road user VR co-simulator be developed and tested to study the behaviors*

and interactions between various vulnerable road users?

Five sub-research questions are formulated to further address the main research question.

- 1) **Simulator integration:** How can various existing VR simulators be effectively linked and integrated into a unified multi-player multi-modal co-simulator?
- 2) **Interaction development:** What types of interactions between different road users should be simulated in VR to achieve a similar level of realism as in the real world?
- 3) **Data collection:** What kinds of data from different road users during a multi-player VR experiment can be collected?
- 4) **Co-simulator assessment:** How to assess the effectiveness of the built VR co-simulator by a multi-player VR experiment?
- 5) **VRU-AV interaction:** How do the number of VRUs, their role, and their initial relative location influence the VRUs' behaviors and their interactions with the AV in shared space?

The structure of the remainder is as follows: Section III begins with a comprehensive review of the relevant literature. Next, Section III introduces the developed multi-player multi-modal VR co-simulator. Section IV describes a multi-player VR experiment as a case study. In Section V, the findings from the data analysis are presented. Section VI answers the research questions and Section VII concludes the thesis.

II. BACKGROUNDS

A. VRU Crossing Behaviors

This section reviews the crossing behaviors of two main groups of VRUs: pedestrians and cyclists, respectively.

1) *Pedestrian Crossing Behaviors:* Pedestrian crossing behavior is a central focus in VRU behavior research and road safety [1]. The complexity of pedestrian crossing behavior arises from the intricate decision-making process involved, which is influenced by a multitude of factors, including individual characteristics [20], [21], human factors [22]–[24], road and traffic conditions [20], [22], and social information use [14], [15], [25].

Individual characteristics are critical in shaping pedestrian crossing behavior. Several individual characteristics including age [20], [26], gender [20], [21], the experience of car accidents [20], and baggage condition [21], have been studied, and identified as factors influencing pedestrians' crossing behaviors and causing potential risky conflicts and dangerous situations. Furthermore, human factors [22] are also considered in pedestrian crossing behaviors, such as risk perception, risk proneness, travel motivation, and attitude towards walking. In addition, external factors such as traffic flow [20], and infrastructure design [20], [22] also significantly impact pedestrian crossing behavior.

Crossing scenarios do not always involve a single pedestrian. Interactions with others, whether as part of a pair [15] or a group [14], [25], also play a significant role in shaping individual behavior patterns during group crossings. For example, [25] reported that neighbors of a crossing pedestrian tended to cross before other waiting pedestrians. It also discovered the

cases in which individuals started to cross and then returned to the roadside, frequently found in groups. In [14], [15], the effect of other pedestrians as the social context was further explored.

With the rapid development of AVs, AVs are expected to be deployed soon, co-existing with HDVs. Hence, pedestrians' interactions with AVs have become a new research focus. Research interests include pedestrian perception of AV [27]–[29], road user behaviors with AV [15]–[17], [19], [30], and eHMI design [12], [14], [30]–[32]. A detailed literature review of pedestrian-AV interaction can be found in [33].

2) *Cyclist Road Behaviors:* Besides pedestrians, cyclists are also another important group of VRUs [1]. The cyclist's road behaviors include not only crossing behaviors, but also other risky operations (i.e., overtaking behaviors), and rule violations [34]. Overall, the road behaviors of cyclists are influenced by several categories of factors, including individual characteristics [7], [35], [36], infrastructure [37], [38], and group dynamics [39], [40]. Understanding these elements is crucial to designing safer and more cyclist-friendly urban infrastructure.

Individual characteristics, such as age [7], [35], gender [7], [35], [36], and experience level [35] significantly influence cyclist crossing decisions. [7] reported male and younger cyclists were found to commit more violations and less positive behaviors compared to female and older ones across three countries (Australia, China, and Colombia). The same conclusions were confirmed by [35], which focuses on a group of young cyclists aged from 15 to 24 in China. The result also revealed the contribution of risk perception and cycling skills to cyclist safety. Meanwhile, the design of road infrastructure and surrounding environmental conditions [37], [38] heavily influence cyclist road safety. More details could be referred from a recent literature review on cyclists' behavior research in [34].

Cyclists' crossing behavior is often shaped by interactions with other road users, including motorists, pedestrians, and cyclists. Cyclists riding in groups behave differently than those riding alone [34], [39]. [39] reported that teamwork factors may make behavioral interventions to decrease risky behaviors easier to implement with group cyclists compared to individual cyclists, thus leading to safer road behaviors.

B. VR Experiment to study VRU-AV Interaction

Recently, VR experiments have gained recognition as a powerful method for studying VRUs' behaviors [11]–[13]. By providing an immersive environment, VR enables participants to interact with virtual traffic scenarios like real-world situations, all while maintaining a high level of safety and collecting the necessary data.

1) *Pedestrian-AV Interaction in VR Experiment:* Numerous VR experiment studies involving AVs concentrate on their interactions with pedestrians. These studies cover aspects such as eHMI design [30], [41], road conditions [15], [17], [42], and driving styles [12], [15], [43].

VR experiment is an efficient and powerful approach to evaluate the effectiveness of different proposed eHMI designs.

First, VR experiments enable the researchers to design more advanced eHMIs with multiple modalities [41] and let the participants experiment with them in a more immersive way [44], compared to other approaches such as online surveys [45], and field studies [46], [47]. For example, [41] investigated the effect of the combination of visual and audible eHMIs on the pedestrian-AV interaction process. In another study [44], the acceleration indication eHMI was assessed in particular to combine the explicit cue of eHMI and implicit cue of vehicle motion. Second, VR experiments allow researchers to investigate the effectiveness of eHMI designs from diverse perspectives [30], [31], [48]. In [30], a motion-based approach was proposed and assessed as a valid implicit investigation method for eHMI designs, aiming to complement the traditional questionnaire and explicit intention confirmation by pressing a button. Furthermore, in [31], the scalability issue of eHMI design was investigated when the AV encounters multiple pedestrians at the same time, which is hard to assess in other assessment approaches [48].

The investigation of road layouts [15], [17], [42] has also been carried out in several VR experimental studies. While the majority of VR studies focus on unsignalized traffic situations with one-lane roads [19], [30], [31] and two-lane roads [18], [32], some other road layouts have been investigated to study their effects on pedestrian-AV interactions. For example, the study by [42] examined how the median influences pedestrian safety and trust in AVs while crossing streets. Meanwhile, [15] compared T-junctions and straight roads to evaluate the effect of road layout on pedestrian crossings. Additionally, [17] compared five different street designs to assess practical interventions for managing collective behavior among pairs of pedestrians.

The AVs significantly impact the interaction between pedestrians and AVs, with kinematic factors such as speed, gap, and deceleration influencing pedestrian crossing behavior. For instance, the study in [12] controlled the speed and gap of a single AV to examine pedestrians' intentions to cross. Another study, [43], explored how these factors affected pedestrians' decisions when faced with a group of AVs. Additionally, [15] investigated how different deceleration profiles of AVs influenced pedestrian reactions to yield signals.

2) *Cyclist-AV Interaction in VR Experiment*: Compared to the popularity of using VR experiments to study the interaction between pedestrians and AVs, studies on cyclist-AV interaction are still scarce [13], [49]. This is due to the difficulty of designing and developing a cyclist simulator with VR headset [50], [51], compared to the pedestrian VR simulator.

eHMI design is investigated in one study [49]. The researchers implemented an immersive VR cyclist-simulator, and designed and evaluated several AV-cyclist interfaces. The results confirmed that AV-cyclist interfaces could improve cyclists' confidence in AV lane-merging scenarios.

In a different study [13], researchers used 360-degree VR video recordings to examine how cyclists decide when to cross paths with an AV and an HDV. By varying factors such as the type of vehicle, its speed, the size of the gap, and the right of way, the study explored how these elements, along with road conditions and driving styles, influenced cyclists'

crossing decisions. The findings indicated that gap size and right of way were the main factors affecting cyclists' crossing intentions, while vehicle type and speed did not significantly impact their decisions.

3) *Multi-player Interaction in VR Experiment*: Although numerous VR experimental studies have been carried out in the literature, the majority involve only one participant interacting with computer-programmed characters [14]. The way participants behave when interacting with a real person can differ from their interactions with computer-generated characters. For instance, [54] observed notable differences in crossing behavior when participants crossed alongside another human participant compared to an NPC in a VR experiment.

Implementing a multi-player, multi-modal VR co-simulator presents several challenges: First, developing multi-player VR environments demands greater technical expertise to maintain stable connections and design dynamic interactions. Achieving a high level of realism is significantly more complex than achieving a high level of realism in single-user pedestrian VR applications, many of which are readily available and easy to use. Consequently, the development timeline for multi-player VR co-simulators is typically much longer. Second, creating VR simulations for other road users is generally more challenging than for pedestrians. Pedestrian-based VR applications remain the most commonly explored in VR research. In contrast, studies focusing on different road user types must build custom simulators tailored to those users, requiring considerable time and effort to ensure feasibility and validated results.

Hence, there is a scarcity of studies examining real-time human-to-human interactions among different types of road users. Only a limited number of studies have explored interactions between various road users [18], [19], [52]. For instance, [18], [19] developed a co-simulator to investigate vehicle-pedestrian interactions. Furthermore, as highlighted in Section II-A, group dynamics play a crucial role in shaping the road behaviors of pedestrians and cyclists. Incorporating multiple participants into VR as a group offers a promising approach to gaining deeper insights into this phenomenon. For example, [15], [17], [53], [54] involved two participants acting as pedestrians crossing the street together. A detailed summary of these studies is provided in Table I.

C. Shared Space

1) *Motivation and Concept*: Many current studies concentrate on standard road settings like intersections [21], [24], [38], street roads [13], [25], and bicycle lanes [55]. These types of road designs are built on the principle of *separation* [56], which is meant to enhance the safety of each group of road users by keeping them apart. However, this principle may not always be suitable as the separation could also lead to unintended consequences [57], [58]. For instance, physical barriers and designated lanes might restrict the flexibility and adaptability of the road space, disrupting the connectivity between living areas. Moreover, the principle of separation may not effectively address the complexities of urban environments where space is limited.

TABLE I: Summary of previous work on multi-player road-user simulators.

Paper	Year	#Players	Road Users Involved	Setup
[52]	2019	2+	Pedestrian-driver	VR headsets
[18]	2023	2	Pedestrian-driver	Driving simulator + CAVE
[19]	2024	2	Pedestrian-driver	Driving simulator + VR headset
[17]	2024	2	Double pedestrians-vehicle	VR headsets
[15]	2024	2	Double pedestrians-AV	2 VR headsets
[53]	2024	2	Double pedestrians-AV	2 VR headsets

A more integrated approach that encourages shared use and mutual awareness among all road users might be more effective in enhancing overall safety and mobility. Shared space [57], [58] is an urban design approach that integrates multiple modes of transportation, such as pedestrians, cyclists, and vehicles, into the same area, without the conventional separation of road users through elements like traffic signals, road markings, or curbs.

2) *VRU-AV Interaction in Shared Space*: Despite the growing interest in shared spaces, research on VRU-AV interactions in shared space remains limited, largely due to the challenges of observing real-world interactions between AVs and VRUs.

Some studies have inferred pedestrian behaviors by examining interactions with various vehicles, and even mobile robots. [28] reviewed interactions with conventional cars, mobile robots, and AVs, highlighting the diverse and imperfect nature of pedestrian actions, and emphasizing the need for AVs to adhere to socially compliant rules. Similarly, [59] analyzed video data to investigate pedestrian responses to AV-like vehicles in shared spaces. However, how VRUs engage with AVs in shared spaces remains uncertain.

One potential approach involves live demonstrations and surveys to engage road users, mainly used for evaluating eHMI designs for AVs [60]. In [61], 664 participants from three European cities completed a questionnaire on Level-4 AVs during live demos, exploring safety perceptions and opinions on AV information displays. [62] studied online interactions with AVs (a car and a bus) in shared spaces using various eHMI strategies. Participants felt safer and more informed with eHMI use, especially with combined strategies, compared to mode awareness alone or no eHMI. Additionally, [27] surveyed 254 cyclists and pedestrians in Australia and the UK about their willingness to cross in front of AVs, feelings of security, and relaxation through an online questionnaire.

VR experiment is also regarded as another approach to investigate VRU-AV interactions in shared spaces [15], [63], [64]. [15] studied pedestrian-AV interactions in these environments, where participants attempted to cross the road under varying conditions, including the presence of another pedestrian, different eHMIs, AV driving styles, and road conditions. In a separate study, [63] examined the behavior of elderly Japanese pedestrians interacting with an AV in a shared space using a CAVE-based VR experiment. [64] investigated the design of eHMIs for different types of AVs for the interaction with pedestrians in shared space.

Overall, despite the interest in VRU-AV interaction studies in shared spaces, most only involve a single pedestrian and often overlook cyclists, a key group of VRUs in these environments.

D. Summary

To summarize, two key research gaps have emerged from this review: First, there is a need for an advanced VR co-simulator capable of supporting multi-player, multi-modal VRU-AV interactions. Second, studies on VRU-AV complex interactions involving multiple road users within shared spaces are scarce.

III. VR CO-SIMULATOR

A. Simulator Integration

1) *Existing Simulators*: The first step in developing the VR co-simulator is to integrate the current pedestrian and cyclist VR simulators. The VR simulators used to integrate into the co-simulator are shown in Figure 1, respectively. These dedicated VR simulators were designed and developed by The Mobility in the eXtended Reality Lab of TU Delft for the research of pedestrian and cyclist behaviors [15].



(a) Pedestrian VR Simulators (b) Cyclist VR Simulator

Fig. 1: The existing pedestrian and cyclist VR simulators in the MXR Lab.

The pedestrian VR simulator offers players two different methods of locomotion. They can use a motion controller to teleport to different locations within the virtual environment. Alternatively, participants can opt for the free-hand locomotion method to navigate the virtual space more freely.

The bike VR simulator uses a stationary setup to replicate the cycling experience for cyclists on the road. This system includes a Garmin TacX Flow bike trainer, an actual bicycle, and a Raspberry Pi, which captures real-time speed and braking inputs.

The VR co-simulator has been developed utilizing Unreal Engine 5 (UE5). UE5 offers integrated support for multi-player gaming, enabling developers to build interactive experiences where multiple players can engage simultaneously in a shared virtual environment.

B. Interaction Development

The body tracking system is essential for achieving real-time, accurate representations of road users' movements and behaviors. By capturing and reproducing natural motion, body-tracking technology enables dynamic and interactive simulations, allowing participants to interact authentically with the virtual environment. To accurately simulate realistic behaviors and interactions among different road users in VR, the priority is to ensure a precise representation of body movements within the virtual environment. Consequently, we implemented a full-body tracking system for pedestrians as the foundational framework for other road users.

The full-body tracking system for pedestrians captures the movement of their head, hands, waist, and feet. This system can be broken down into several components: head, spine (waist), hands, and feet. For the head, a VR headset tracks its position and orientation, making it the simplest element of the implementation. This is represented by the yellow circle around the avatar's head. Spine movement is tracked using a single tracker, which controls the overall movement of the spine. The motion originates from the tracker at the bottom, represented by the yellow hexagon, and propagates upward through the spine. The hands and feet are tracked using inverse kinematics, enabling precise representation of their movements within the VR environment.

The cyclist body-tracking system builds upon the pedestrian full-body implementation but focuses solely on the upper body, as the feet typically remain on the pedals. As a result, the cyclist's animation combines real-time tracking with pre-defined animations. A key distinction between cyclist and pedestrian tracking is the requirement for cyclists to grip the bike's handlebars, ensuring they appear to be cycling rather than floating. To achieve this, the hand-mounted trackers are used to monitor whether the hands are in contact with the handlebars.



Fig. 2: The MetaHuman characters in VR co-simulator.

Along with utilizing body tracking to replicate the dynamic movements of road users, it is equally crucial to give them a lifelike human appearance when they are introduced into the VR environment. As shown in Figure 2 presents a technology called MetaHuman, which is used to fulfill this requirement.

C. Data Collection

The ultimate goal of establishing this VR co-simulator is to gather data on the behaviors and interactions of different road users via the VR experiments. We highlight the trajectory and behavioral data that the VR simulator is capable of collecting, respectively.

1) *Trajectory data*: Trajectories include the fundamental information about the road users' behaviors [65]. A collection of the important objective metrics can be derived from the trajectory data. Therefore, the VR co-simulator should be able to save the trajectory data.

In the implementation, the trajectory data is collected to precisely track the positions and movements of participants throughout the virtual environment. This data set includes real-time updates of spatial coordinates and velocities, ensuring an accurate depiction of both pedestrian and cyclist paths. The data is sampled at a high frequency to maintain a detailed and reliable record of movement patterns.

2) *Behavioral data*: Besides trajectory data, more VRUs' behavioral data can be gathered via VR experiments and provide more insights into the VRUs' decision-making process. As [4] reported, VRUs also rely on implicit communications, such as eye contact and gestures to negotiate with the vehicles. Furthermore, [30] confirmed that body movement can also be linked with the pedestrians' decision-making process. Therefore, it is beneficial to consider including these behavioral data in the data collection framework of the VR co-simulator.

The HTC Vive Pro Eye VR headset, equipped with integrated eye-tracking technology, provides detailed insights into participants' visual attention. The system records data such as gaze origin and direction, enabling researchers to identify specific objects or elements participants focus on during interactions in the virtual environment. While the device is capable of collecting additional information, such as pupil diameter and blink status, these data are currently inaccessible within UE5. As a result, this portion of eye-tracking data will not be included in the upcoming VR experiment.

The body-tracking system detailed in Section III-B enables the collection and storage of comprehensive movement data for pedestrians and cyclists. This system records the precise spatial coordinates and orientation of each tracker used in the VR simulator. The spatial data includes x, y, and z positions measured in centimeters, while orientation is captured as pitch, yaw, and roll angles in degrees. For pedestrians, six trackers are utilized to monitor the entire body, including the head, waist, hands, and feet. For cyclists, the focus is on the upper body, with trackers placed on the head and hands.

IV. METHODOLOGY

This VR experiment has two aims. First, the design and development of the multi-player, multi-modal VR co-simulator is assessed. Second, the effect of the role of VRUs, the number of VRUs, and the initial location of VRUs on the VRUs' behaviors and their interactions with the AV in the shared space is investigated. A within-subject design approach was used in the current study to remove the effects of individual differences.

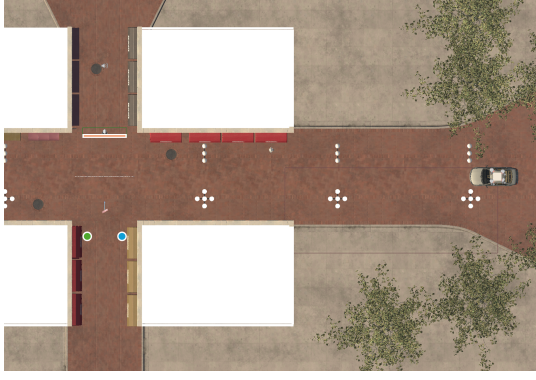


Fig. 3: The eye-bird view of the established VR scenario. The green and blue circles indicate the farther and closer starting location. The orange bar indicates the destination of the crossing.

A. Experiment Scenario Design

One existing shared space, intersected by the Oude Langendijk and the Jacob Gerritstraat near the New Church in Delft, The Netherlands, was chosen and modified to construct the VR environment. In this shared space environment, there were no traffic lights, no stop signs, no pedestrian zebra, or any other elements to indicate the right of way. An audio soundscape was added to the VR environment to enhance the realism of the VR experience. The landscape of the established VR scenario is shown in Figure 3. In Figure, the green and blue circles indicate the farther and closer starting location, respectively. The orange bar indicates the destination of the crossing.

1) *Experiment Factors*: Three within-subject variables were included in this VR experiment: the number of VRUs (i.e., 1, 2), the role of VRUs (i.e., pedestrian or cyclist), and the initial location relative to the AV (i.e., far away or close to the AV). A detailed description of each variable is provided below.

2) *Number of VRUs*: Based on the research question, this study aims to explore the interaction between multiple real human road users through VR. To achieve this, both single-VRU and multiple-VRU crossing tasks were developed. In the single-VRU crossing task, participants take on the role of either a pedestrian or a cyclist. In the multiple-VRU crossing task, two participants cross the street together.

3) *Role of VRUs*: In addition to the number of VRUs, participants cross the street in distinct roles. Pedestrians and cyclists, as common road users in shared spaces, are included in the experiment. In the single-VRU tasks, participants take turns playing as a pedestrian and a cyclist. In the multiple-VRU tasks, two participants cross the street together, either as two pedestrians or as one pedestrian and one cyclist.

4) *Relative Location to AV*: Since the shared space being studied is a relatively narrow street with a width of about 5 meters, visibility is a common concern. To explore the impact of relative locations of VRUs on the interaction between VRUs and AV, the distance gap was included as the final variable to manipulate in the experiment. In the single-VRU experiment,

participants start from two different positions, located 1.5 meters to the left and right of the street's centerline. In the multiple-VRU experiment, the two participants start from the same positions as in the single-player scenario, maintaining an initial distance of 3 meters between them. Initially, a 4-meter distance between the two VRUs was selected to balance avoiding proximity that could encourage group behavior, while still ensuring that the eHMI yielding message would be relevant to both pedestrians, following the approach of [15]. However, this distance was later reduced to 3 meters to ensure safe walking movement within the experiment room while using VR, as the room is 5 meters wide and equipped with base stations mounted on tripods along the walls and windows side.

B. Experiment Task Design

The combination of all variables led to a total of 10 road-crossing scenarios, which were organized into four blocks, as shown in Table III.

TABLE II: Tasks and blocks included in the VR experiment.

Task	Block	#VRU	Role of VRU	Initial Location
1	I	1	Ped	Far
2		1	Ped	Close
3	II	1	Cyc	Far
4		1	Cyc	Close
5	III	2	Ped⊕Ped	Far⊕Close
6		2	Ped⊕Ped	Close⊕Far
7	IV	2	Ped⊕Cyc	Far⊕Close
8		2	Ped⊕Cyc	Close⊕Far
9		2	Cyc⊕Ped	Far⊕Close
10		2	Cyc⊕Ped	Close⊕Far

Ped denotes pedestrian.

Cyc denotes cyclist.

Far denotes the starting location far away from AV.

Close denotes the starting location close to AV.

⊕ serves as the delimiter, with the symbol before representing player 1 and the symbol after representing player 2.

1) *Block I (Single Pedestrian Crossing)*: This block comprises two single-pedestrian crossing scenarios. These scenarios are designed to investigate the behaviors of pedestrians as they navigate the street from distinct starting positions. This allows for a detailed analysis of decision-making processes in urban environments, particularly focusing on individual pedestrian actions.

2) *Block II (Single Cyclist Crossing)*: This block features two single-cyclist crossing scenarios, which aim to examine the crossing behaviors of cyclists at intersections. Similar to Block I, the scenarios emphasize the independent crossing experiences of cyclists, providing insights into their specific interactions with the environment.

3) *Block III (Dual Pedestrian Crossing)*: This block includes two double-pedestrian crossing scenarios. In these scenarios, two pedestrians cross the street concurrently, facilitating an exploration of their interactions and the subsequent effects on their decision-making processes. This block aims to elucidate the dynamics of pedestrian interactions in shared spaces.

4) *Block IV (Pedestrian-cyclist Joint Crossing)*: This block focuses on pedestrian-cyclist joint crossing scenarios. In these scenarios, both pedestrians and cyclists engage in crossing the street simultaneously, thereby allowing for an examination of the interactions and responses among different road users in a mixed-use context.

The scenarios differed only in the within-subject variables, while the rest of the environment, such as infrastructure, surrounding buildings, and sounds, remained unchanged. In all blocks, the AV consistently yielded to participants, although this behavior was not explicitly communicated to them.

5) *AV Setup*: Besides participants, AV setup is also important for the experiment design. In all scenarios, the AV started to approach the pedestrian from 30 meters away at a speed of 15 km/h following the speed limit of shared space in the Netherlands.

The deceleration profile involved only a single phase of deceleration. When the distance between the AV and the VRU reaches 15 meters, the AV begins to decelerate from 15 km/h to 5 km/h at a rate of 2.5 m/s^2 and then continues at 5 km/h. The AV comes to a complete stop 3 meters away from the pedestrians. This deceleration style was also employed in a previous study [15] to examine how deceleration affects pedestrian crossing behaviors. It is considered more effective because it is defensive, allowing the early braking to better communicate the AV's yielding intention, thereby reducing pedestrians' decision time to cross the road.



(a) When AV detects VRU, eHMI turns green (b) eHMI keeps red when AV moves in motion normally

Fig. 4: The light-based eHMI on AV and its meaning.

To further indicate that the approaching vehicle is an AV, an eHMI has been specifically designed on top of the vehicle to convey its intentions. The eHMI is light-based. When the light turns green, it indicates that the AV has detected the VRU and is willing to yield the right of way. Conversely, a red light signifies the opposite. The appearance of the AV with eHMI is illustrated in Figure 4.

C. Experimental Apparatus

1) *Room Setup*: The VR experiment was conducted in Mobility in eXtended Reality Lab, Room 6.98, within the Faculty of Civil Engineering and Geosciences at TU Delft, from Monday, October 14th to Friday, October 26th, 2024. The room measured approximately 11 meters in length, 5 meters in width, and 3 meters in height. It was split into two sections, each simulating a crossing scenario for pedestrians and cyclists. All four blocks of VR experiments were held in this single room.

2) *VR Hardware*: To provide the VR experience and enable interaction during the experiment, two HTC Vive Pro Eye headsets (Resolution: 1440×1600 pixels per eye, 2880×1600 pixels combined, Field of view: 110 degrees, Refresh rate: 90 Hz) along with their standard motion controllers were used. Three Vive Tracker 3.0 devices were attached to different body parts of each participant for body tracking. To allow unrestricted movement within the room, each headset was equipped with a wireless adapter, enabling a wireless connection, while the link boxes were connected to the workstation PC positioned in the corner of the room. Six base stations were strategically placed around the perimeter to ensure full tracking coverage of both the headsets and body trackers. The two headsets were wirelessly connected to two separate Windows 10 desktops. Each desktop was equipped with an AMD Ryzen 9 7900X 12-Core Processor, 32 GB of RAM, an NVIDIA GeForce RTX 4090 graphics card, and a Samsung 990 PRO 4 TB SSD.

D. Experiment Procedure

The VR experiment procedure comprises four distinct stages: (1) introduction of the experiment, (2) calibration and familiarization with the VR locomotion, (3) official experiment, and (4) filling in the post-questionnaire. The following sections provide a more detailed explanation of these four stages:

E. Data collection

1) *Objective Data*: Throughout the formal experiment, the experimental software continuously captured and logged various objective measurements in real time. These included participants' movement paths, eye movements, and body positions. All this data was automatically stored in the CSV file format for subsequent analysis. All data were captured at an approximate frequency of 40 Hz.

2) *Subjective Data*: There are eight sections in the post-experiment questionnaire. The eight sections cover the participant information, system usability [66], simulator sickness [67], realism [68], presence [69], trust in AV [70], perceived behavior control and risk [12], and feedback. The results of the questionnaires will be compared with the previous study [15].

F. Data Analysis

1) *Metrics Definitions*: The following metrics are calculated based on the three categories of datasets:

- Negotiation time $T_{negotiation}$ (s) is the period a VRU remains in negotiation before starting to cross, beginning from the moment the experiment is triggered (when the player presses the button on the motion controller to start the game).
- Crossing time $T_{crossing}$ (s) is defined as the duration for the VRU to reach the other side of the road from the moment they begin crossing.
- Space gap D_{gap} (m) is the longitudinal distance between the AV and the VRU when the VRU starts to cross.

- Total distance D_{total} (m), refers to the entire distance covered by the VRU during the road crossing.
- Average speed V_{total} (m/s) is the mean speed during the task, calculated by dividing the total traveling distance by the total traveling time.
- AV-gazing time T_{AV} (s), is aggregated by the collected eye-gazing data and means the total duration of gazing on the AV during the whole crossing process.

2) *Model Formulation*: The linear mixed model (LMM) was employed to study the influence of the selected factors including the VRU combination and starting location on the crossing behavior of different VRUs, based on the processed objective measures. LMM is particularly advantageous in accounting for both fixed effects, such as experimental conditions, and random effects, such as individual variability and repeated measurements within subjects, making it well-suited for analyzing complex, hierarchical data structures.

$$\begin{aligned}
 T_{negotiation}/T_{crossing}/D_{gap}/V_{total}/D_{total}^{ped}/T_{AV}^{ped} \\
 \sim \mu_{Block} + \mu_{Loc} + \\
 \mu_{Block} \times \mu_{Loc} + \\
 (1|\psi_{pair}) + (1|\psi_{pair} : \psi_{player})
 \end{aligned} \quad (1)$$

3) *Dependent Variables*: The model formulations of LMM were defined in Equation (1) using Wilkinson notation [71]. Several dependent variables, namely negotiation time $T_{negotiation}$, crossing time $T_{crossing}$, space gap D_{gap} , average speed V_{total} , total walking distance D_{total}^{ped} , and AV-gazing time T_{AV}^{ped} were modeled separately, as shown in the first row of the Equation (1). Dependent variables without the superscript *ped* refer to separate versions modeled for pedestrians and cyclists. The total walking distance and AV-gazing time were calculated exclusively for pedestrians, with the indication of the superscript *ped*. This is because cyclists, who cannot steer, have uniform distances, and the sample size (around 10 in the fourth block) for their eye-gazing data is insufficient.

4) *Fixed Effects*: The LMM is formulated as a function of the VRU combination μ_{Block} , the starting location μ_{Loc} , and the interaction term between μ_{Block} and μ_{Loc} , which are included as fixed effects in the model, as shown in the second and third rows of Equation (1). The levels of the variable μ_{Block} differ in the LMM based on the role of the road users (pedestrians or cyclists). For pedestrian-related metrics, the VRU combination μ_{Block} has three levels, corresponding to Blocks 1, 3, and 4 in the VR experiment, with Block 1 (single-pedestrian crossing) serving as the reference level. For cyclist-related metrics, there are only two levels, as participants acted as cyclists exclusively in Blocks 2 and 4, with Block 2 (single-cyclist crossing) as the reference level. The variable μ_{Loc} represents the starting locations of the VRU in each task, indicating whether they began closer to or farther from the AV. This variable μ_{Loc} retains two levels in both pedestrian and cyclist LMM formulations and the starting location farther from the AV is the reference level.

5) *Random Effects*: In addition, random effects were included to account for the complex data structures introduced

by the multi-player experimental design. Both the pair ID ψ_{pair} and player ID ψ_{player} are taken into account, as shown in the last line of Equation (1). Specifically, the first random-effect term $(1|\psi_{pair})$ accounts for the variability between different pairs of two participants. Since each pair may have unique characteristics that affect their crossing behavior, this random effect helps capture the inter-pair variability. And the second random-effect term $(1|\psi_{pair} : \psi_{player})$ accounts for the variability within individual players in each pair. This term allows for modeling the fact that players within the same pair might exhibit different behaviors, thus capturing the intra-pair variability.

G. Participants

Participants were recruited using three approaches: (1) sharing information through various social media platforms, including LinkedIn, WhatsApp, and WeChat; (2) sending announcements via departmental email lists managed by secretaries from different faculties at TU Delft; and (3) distributing flyers placed around the TU Delft campus. Participants had two options for joining the VR experiment: they could either participate as a pair with a friend or colleague, or they could choose to participate individually, in which case they would be paired with an unfamiliar participant. The participant did not receive any compensation for their participation in the study. The study was approved by the Human Research Ethics Committee of the Delft University of Technology (Reference ID: 4607). 40 participants (20 pairs) took part in the VR experiment. All participants had normal or corrected vision and normal mobility. All participants' characteristics are shown in Table XVI. No participants withdrew from the experiment due to motion sickness.

V. RESULTS

A. Dataset Summary

Objective data collected from the VR experiment include trajectory data, body-tracking data, and eye-gaze data. Table III summarizes the sample sizes for each data category across pedestrians and cyclists.

During the formal experiment, all participants participated in the single-player scenarios (blocks 1 and 2). However, in the double-pedestrian crossing scenario (block 3), data for one pair of participants were not recorded due to a base station detection failure. Additionally, one pair of participants did not complete the final block (block 4) of the pedestrian-cyclist joint crossing tasks due to time constraints. As a result, the trajectory and body-tracking datasets comprise 392 samples, including 235 pedestrian trajectories and 157 cyclist trajectories.

Eye-tracking data was also collected during the VR experiment. However, due to hardware and software issues, some participants' eye-tracking data were not successfully recorded or saved. Nonetheless, the remaining dataset, comprising approximately 30 pedestrians, is still sufficient for studying pedestrian eye-gazing behaviors during crossing in the shared space. In contrast, most of the cyclists' eye-gazing data in the multi-player blocks was lost due to the failure of eye-tracking.

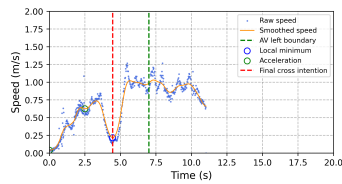
TABLE III: Sample sizes for the trajectory, body-tracking, and eye-gazing datasets.

Role of VRU	Combination	Initial Location	Sample Size		
			Trajectory	Body-tracking	Eye-gazing
Pedestrian	Block 1	Far	40	40	31
		Close	40	40	33
	Block 3	Far	39	39	29
		Close	39	39	29
	Block 4	Far	38	38	28
		Close	39	39	29
	Overall	Overall	235	235	179
Cyclist	Block 2	Far	40	40	24
		Close	40	40	21
	Block 4	Far	39	39	11
		Close	38	38	10
	Overall	Overall	157	157	66

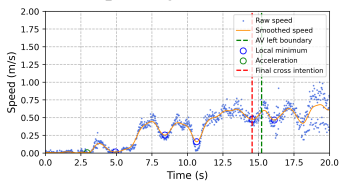
Besides, all the participants also filled in the post-experiment questionnaire.

B. Data Processing

The pedestrians' speed profiles, derived from trajectory data, were smoothed using a one-dimensional Gaussian filter with a standard deviation of 12 for the Gaussian kernel. These refined profiles were then analyzed to identify the timestamp corresponding to the final crossing intention. As illustrated in Figure 5, two examples of the speed profiles demonstrate the data processing steps. To pinpoint the crossing intention point, all behavioral change points were first categorized into three types: lowest speed points, acceleration points, and deceleration points. The crossing intention point was defined as the final behavioral change point occurring before the pedestrian entered the area directly in front of the AV, as indicated by the green vertical line in Figure 5.



(a) A simple negotiation with AV.



(b) A complex negotiation with AV.

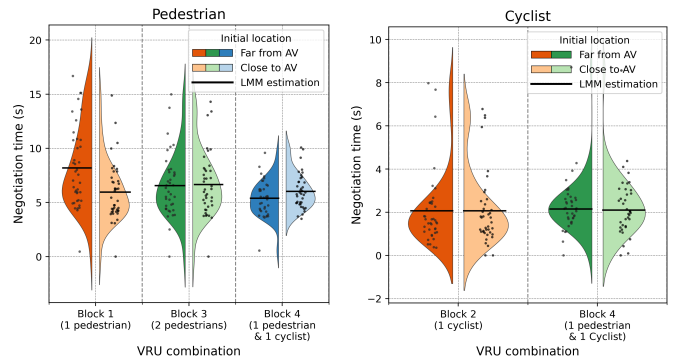
Fig. 5: Speed profiles of the pedestrians.

C. Objective Measures

In this section, six distinct objective measures were derived from the datasets, and LMMs were employed to examine these six objective measures to analyze the behavior of VRUs and their interaction with the AV in shared space.

1) *Negotiation Time*: The LMM analysis for negotiation time is provided in Table IV. The distributions of negotiation time for pedestrians and cyclists are illustrated in Figure 6 via a combination of violin and strip plots.

The LMM analysis revealed significant fixed effects on pedestrians' negotiation time across different VRU combinations and initial relative locations to AV. The intercept was 8.192 seconds, representing the average negotiation time for a single pedestrian starting from a farther location relative to the AV. VRU crossing in pairs significantly influenced pedestrians' negotiation time. In scenarios involving two pedestrians crossing together, the negotiation time was reduced by 1.643 seconds compared to the single-pedestrian scenario. When the VRU combination included a pedestrian-cyclist pair, the pedestrian's negotiation time further decreased by 2.809 seconds. The initial location also played a significant role. Starting closer to the AV significantly reduced the negotiation time by 2.233 seconds. Interaction terms revealed a moderating effect of the initial location on VRU combinations: For dual-pedestrian scenarios, the reduction in negotiation time associated with starting closer to the AV was moderated, resulting in a slight increase in negotiation time. Similarly, in pedestrian-cyclist pairs, starting closer to the AV moderated the reduction in negotiation time with another slight increase.



(a) Pedestrian

(b) Cyclist

Fig. 6: The negotiation time distributions

In contrast, the LMM for cyclists showed a lower baseline negotiation time with an intercept of 2.068 seconds. However, none of the fixed effects, including VRU combinations or

TABLE IV: Summary of the LMM analysis for the negotiation time of the pedestrian and cyclist.

Pedestrian				Cyclist			
Fixed effects	Est.	SE	p-value	Fixed effects	Est.	SE	p-value
β_0	8.192	0.452	<0.001	β_0	2.068	0.258	<0.001
$\mu_{Block:ped} \oplus ped$	-1.643	0.524	0.002	$\mu_{Block:ped} \oplus cyc$	0.077	0.295	0.794
$\mu_{Block:ped} \oplus cyc$	-2.809	0.528	<0.001	$\mu_{Loc:close}$	0.001	0.277	0.998
$\mu_{Loc:close}$	-2.233	0.520	<0.001	$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	-0.044	0.396	0.912
$\mu_{Block:ped} \oplus ped \times \mu_{Loc:close}$	2.340	0.740	0.002				
$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	2.864	0.743	<0.001				
Random effects	Var	SD	p-value	Random effects	Var	SD	p-value
$\psi_{pair} : \psi_{player}$	0.607	0.779	0.117	$\psi_{pair} : \psi_{player}$	0.679	0.824	0.005
ψ_{pair}	1.077	1.038	0.058	ψ_{pair}	0.222	0.471	0.474
Residual	5.407	2.325		Residual	1.537	1.240	
Model				Model			
Observations	235			Observations	157		
Marginal R^2	0.0996			Marginal R^2	0.0004		
Conditional R^2	0.3134			Conditional R^2	0.3698		
logLik	-550.6			logLik	-278.9		
AIC	1119.3			AIC	571.7		
BIC	1150.4			BIC	593.1		

initial locations, were statistically significant. This suggests that cyclists' negotiation time remained relatively stable under all experimental conditions.

For pedestrians, the LMM analysis not only confirms the previous studies [14], [15], [25], which demonstrate that a pedestrian's movement dynamics can be influenced by neighboring pedestrians when crossing as part of a group but also extend this understanding to mixed groups of pedestrians and cyclists, yielding similar results. In contrast, cyclists' behaviors were largely unaffected, aside from slight adjustments in space gaps. This indicates that cyclists are less likely to exhibit behavioral changes when crossing as part of a group. We interpret this as indicating that pedestrians and cyclists may perceive the presence of other VRUs differently in terms of group association. For instance, [72] found that cyclists often adjust their paths to 'weave around' pedestrians, emphasizing their preference for independence. Similarly, [55] observed that pedestrians and cyclists tend to naturally segregate when traveling in the same direction within shared lanes.

While most findings in our study align with previous research [14], [25], some observed collective behaviors differed in [15]. Notably, we found that the negotiation time for the pedestrian farther from the AV decreased significantly when crossing with another VRU, contrasting with the increment in [15]. This quicker decision-making aligns more closely with real-world observations [14] and other VR experiments involving full-body-represented pedestrians [32]. The explanation provided in [15]—that pedestrians were distracted—may stem from the limited body representation (head and shoulders only) used in that study, unlike the full-body representation in ours. Furthermore, the similar negotiation times observed between paired VRUs in our study suggest that collective behavior fosters a synchronized crossing pattern, consistent with findings in [16].

2) *Crossing Time*: Table V presents the LMM analysis of crossing time for pedestrians and cyclists, respectively. The distributions of their crossing times are visualized in Figure 7.

The LMM result reveals that both the number and role of the VRU, as well as the initial relative location to the AV, do not

have a statistically significant influence on the crossing time for pedestrians and cyclists. This indicates that the crossing behavior, in terms of the time to cross, remains consistent irrespective of the number of VRUs or their initial positions relative to the AV.

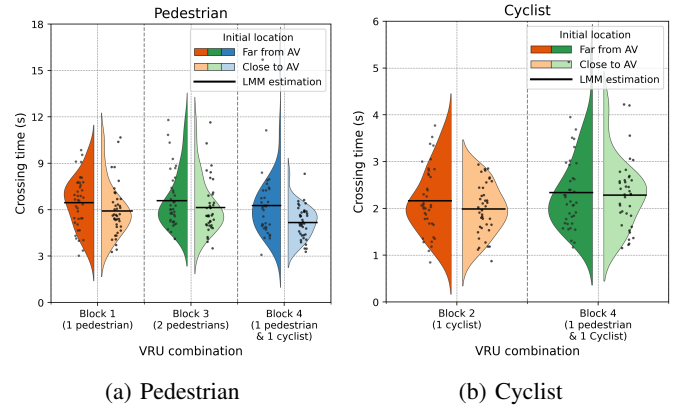


Fig. 7: The crossing time distributions.

Our findings align with the results of the previous study [15], which examined two pedestrians crossing together in a shared space. This consistency suggests that the primary interaction between VRUs and the AV occurs during the negotiation phase, rather than the crossing phase. Moreover, it verifies that cyclists, as another category of VRUs, demonstrate a similarly consistent behavior when interacting with the AV during the crossing phase.

3) *Space Gap*: The LMM analysis of the space gap is summarized in Table VI. Figure 8 presents the corresponding space gap distributions for pedestrians and cyclists, respectively.

For pedestrians, the baseline scenario, in which a single pedestrian started far from the AV, estimated the space gap at 13.297 meters, representing the average distance at which a pedestrian initiated a crossing decision. In more complex scenarios, such as dual-pedestrian or pedestrian-cyclist pairs, the space gap increased significantly by 3.152 meters and 3.323 meters, respectively. Proximity to the AV is another

TABLE V: Summary of the LMM analysis for the crossing time of the pedestrian and cyclist.

Pedestrian				Cyclist			
Fixed effects	Est.	SE	p-value	Fixed effects	Est.	SE	p-value
β_0	6.456	0.281	<0.001	β_0	2.162	0.114	<0.001
$\mu_{Block:ped} \oplus ped$	0.121	0.342	0.725	$\mu_{Block:ped} \oplus cyc$	0.176	0.153	0.252
$\mu_{Block:ped} \oplus cyc$	-0.192	0.345	0.578	$\mu_{Loc:close}$	-0.176	0.150	0.245
$\mu_{Loc:close}$	-0.546	0.340	0.110	$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	0.123	0.215	0.569
$\mu_{Block:ped} \oplus ped \times \mu_{Loc:close}$	0.101	0.484	0.835				
$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	-0.547	0.485	0.261				
Random effects	Var	SD	p-value	Random effects	Var	SD	p-value
$\psi_{pair} : \psi_{player}$	0.285	0.534	0.073	$\psi_{pair} : \psi_{player}$	0.021	0.145	0.649
ψ_{pair}	0.277	0.527	0.182	ψ_{pair}	0.025	0.158	0.549
Residual	2.309	1.520		Residual	0.451	0.672	
Model				Model			
Observations	235			Observations	157		
Marginal R^2	0.0693			Marginal R^2	0.0358		
Conditional R^2	0.2516			Conditional R^2	0.1245		
logLik	-448.7			logLik	-166.6		
AIC	915.3			AIC	347.2		
BIC	946.5			BIC	368.6		

TABLE VI: Summary of the LMM analysis for the space gap of the pedestrian and cyclist.

Pedestrian				Cyclist			
Fixed effects	Est.	SE	p-value	Fixed effects	Est.	SE	p-value
β_0	13.297	0.694	<0.001	β_0	14.748	0.620	<0.001
$\mu_{Block:ped} \oplus ped$	3.152	0.838	<0.001	$\mu_{Block:ped} \oplus cyc$	4.945	0.735	<0.001
$\mu_{Block:ped} \oplus cyc$	3.323	0.844	<0.001	$\mu_{Loc:close}$	-1.599	0.700	0.0242
$\mu_{Loc:close}$	1.663	0.832	0.047	$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	0.866	0.999	0.389
$\mu_{Block:ped} \oplus ped \times \mu_{Loc:close}$	-4.286	1.185	<0.001				
$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	-2.958	1.189	0.014				
Random effects	Var	SD	p-value	Random effects	Var	SD	p-value
$\psi_{pair} : \psi_{player}$	0.229	0.478	0.784	$\psi_{pair} : \psi_{player}$	0.679	0.824	0.043
ψ_{pair}	2.587	1.609	0.018	ψ_{pair}	0.222	0.471	0.363
Residual	13.856	3.722		Residual	1.537	1.240	
Model				Model			
Observations	235			Observations	157		
Marginal R^2	0.083			Marginal R^2	0.0004		
Conditional R^2	0.238			Conditional R^2	0.3698		
logLik	-655.2			logLik	-278.9		
AIC	1328.3			AIC	571.7		
BIC	1359.4			BIC	593.1		

critical factor in pedestrians' decision-making process. When a pedestrian started closer to the AV, the space gap increased by 1.663 meters, indicating greater caution close to the AV. However, the interaction between the VRU combination and the initial location shows more nuanced results. Specifically, in dual-pedestrian and pedestrian-cyclist scenarios, starting closer to the AV resulted in a reduction of the space gap of 4.286 meters for dual pedestrians and 2.958 meters for pedestrian-cyclist pairs.

For cyclists, the baseline scenario, where a single cyclist started far from the AV, estimated the space gap at 14.75 meters, reflecting the distance at which cyclists typically signaled their crossing intention. In pedestrian-cyclist pair scenarios, the space gap increased significantly by 4.94 meters, suggesting that the presence of an additional VRU elevated interaction complexity, prompting earlier crossing decisions. In contrast, starting closer to the AV reduced the space gap by 1.60 meters.

These findings suggest that the presence of another VRU may lead both pedestrians and cyclists to initiate their cross-

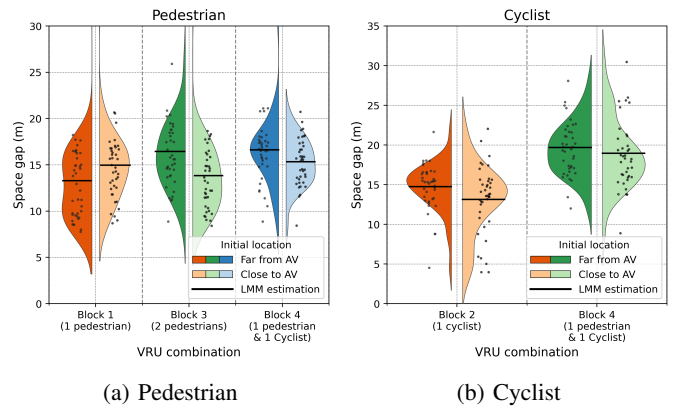


Fig. 8: The space gap distributions.

ing decision earlier. The presence of multiple VRUs likely encourages VRUs to exhibit the crossing intention earlier, thus reducing the time to negotiate and wait. This pattern of earlier crossing behavior is also reflected in the corresponding

negotiation time data shown in Table IV.

4) *Average Speed*: Table VII provides a summary of the LMM analysis of average speeds for both pedestrians and cyclists. The distributions of average speeds for both pedestrians and cyclists are illustrated in Figure 9.

Pedestrian behavior exhibited notable patterns in average walking speeds. The baseline speed of approximately 0.612 m/s was statistically significant. Interestingly, the co-existence of another VRU led to a higher average walking speed for pedestrians. While the presence of another pedestrian did not substantially alter this speed (0.041 m/s), encountering a cyclist leads to a marked increase of 0.100 m/s. The initial position of pedestrians also proved influential, with those starting close to the AV demonstrating significantly higher speeds compared to their opposite-side counterparts. However, the initial location appeared to be moderated in certain VRU combinations, as evidenced by significant interaction effects. When paired with either another pedestrian or a cyclist, and starting close to the AV, pedestrians showed a slight decrease in speed, with estimates of -0.085 and -0.086, respectively.

In contrast, cyclists maintained a higher baseline average speed of 2.217 m/s, which was also statistically significant. However, their speeds remained largely unaffected by VRU combinations or starting positions. Unlike pedestrians, cyclists did not exhibit significant variations in speed across different conditions, including interactions with other VRUs or variations in their initial location. This consistency in cycling speed reflected a more uniform approach to crossing behavior among cyclists compared to pedestrians.

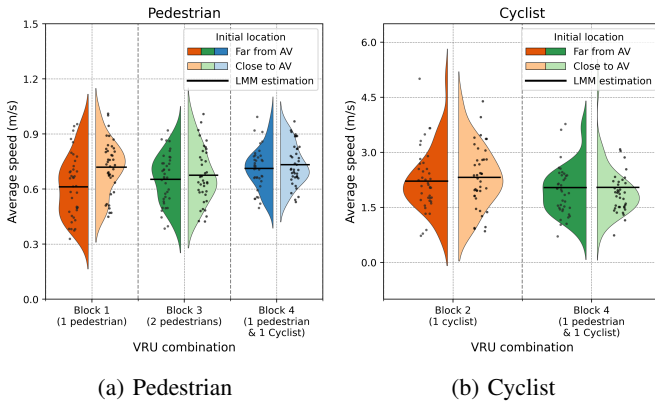


Fig. 9: The average speed distributions.

Compared to the literature [15], [17], which shows a decrease in the average crossing speed of two pedestrians as a pair, our results indicate that the speeds of two pedestrians converge to a similar level, with the pedestrian further away increasing their speed and the pedestrian closer decreasing theirs. This convergence was also observed when accompanied by a cyclist.

There are two possible explanations: Firstly, the familiarization of participants with VR may lead to a particularly low speed for the single pedestrian at the farther position, making it inconsistent with the literature. Secondly, pedestrians starting at a farther location may not feel as pressed by the AV and adopt a relatively relaxed walking style. However, the presence

of another VRU may encourage the participant to consider social information and cross as a group.

5) *Pedestrian's Total Distance*: Table VIII provides a summary of the LMM results for pedestrians' total walking distance. Figure 10 illustrates the total walking distance of pedestrians across various VRU combinations and starting locations.

Based on the analysis, the intercept is 8.238 meters and is highly significant, representing the baseline walking distance when all other factors are at their reference levels. A significant effect of pedestrian-cyclist joint crossing indicates that pedestrians walked less distance in Block 4 compared to the reference level. The effect of double-pedestrian crossing and the closer location are not statistically significant at the 0.05 level, although the closer location shows a trend towards significance. The interactions between VRU combinations and locations are also not significant, suggesting that the effect of locations does not significantly vary across blocks.

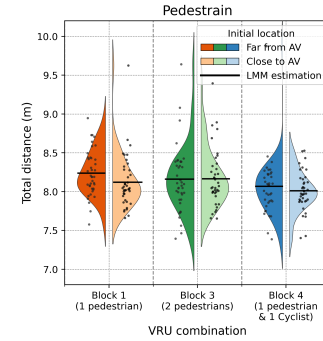


Fig. 10: The distributions of pedestrians' total distance.

Although the effect of an accompanying pedestrian on the total walking distance was not significant in our study, a decrease was observed. A similar significant trend was reported in [15], supporting the explanation that two pedestrians follow the shortest path when crossing the road. Additionally, we extend this explanation to cyclists, demonstrating that their presence exerts a greater regulatory effect on pedestrian walking direction, as shown in Figure 11.

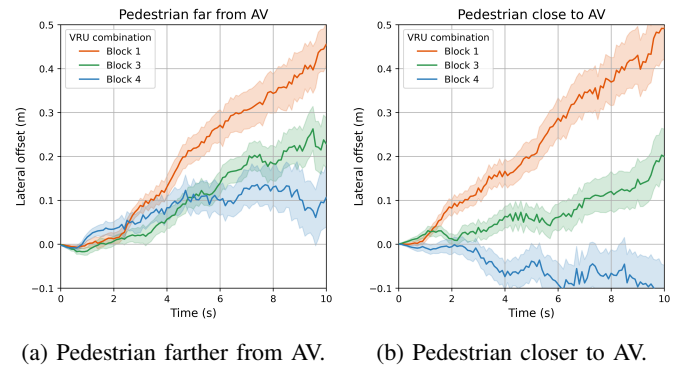


Fig. 11: Lateral offsets of pedestrians from the origin during the crossing. The shaded area represents the 95% confidence interval.

TABLE VII: Summary of the LMM analysis for the average speed of the pedestrian and cyclist.

Pedestrian				Cyclist			
Fixed effects	Est.	SE	p-value	Fixed effects	Est.	SE	p-value
β_0	0.612	0.025	<0.001	β_0	2.217	0.128	<0.001
$\mu_{Block:ped} \oplus ped$	0.041	0.021	0.055	$\mu_{Block:ped} \oplus cyc$	-0.180	0.151	0.234
$\mu_{Block:ped} \oplus cyc$	0.100	0.021	<0.001	$\mu_{Loc:close}$	0.102	0.142	0.476
$\mu_{Loc:close}$	0.107	0.021	<0.001	$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	-0.096	0.203	0.635
$\mu_{Block:ped} \oplus ped \times \mu_{Loc:close}$	-0.085	0.030	0.005				
$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	-0.086	0.030	0.005				
Random effects	Var	SD	p-value	Random effects	Var	SD	p-value
$\psi_{pair} : \psi_{player}$	0.004	0.066	<0.001	$\psi_{pair} : \psi_{player}$	0.166	0.407	0.015
ψ_{pair}	0.006	0.075	0.019	ψ_{pair}	0.042	0.204	0.551
Residual	0.009	0.094		Residual	0.402	0.634	
Model				Model			
Observations	235			Observations	157		
Marginal R^2	0.0873			Marginal R^2	0.0232		
Conditional R^2	0.5713			Conditional R^2	0.3556		
logLik	183.7			logLik	-172.1		
AIC	-349.4			AIC	358.2		
BIC	-318.3			BIC	379.6		

TABLE VIII: Summary of the LMM analysis for pedestrians' total distance.

Fixed effects	Est.	SE	p-value
β_0	8.238	0.057	<0.001
$\mu_{Block:ped} \oplus ped$	-0.078	0.063	0.213
$\mu_{Block:ped} \oplus cyc$	-0.171	0.063	0.008
$\mu_{Loc:close}$	-0.118	0.062	0.059
$\mu_{Block:ped} \oplus ped \times \mu_{Loc:close}$	0.123	0.089	0.165
$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	0.062	0.089	0.486
Random effects	Var	SD	p-value
$\psi_{pair} : \psi_{player}$	0.034	0.186	<0.001
ψ_{pair}	0.009	0.094	0.485
Residual	0.077	0.278	
Model			
Observations	235		
Marginal R^2	0.042		
Conditional R^2	0.386		
logLik	-61.6		
AIC	141.3		
BIC	172.4		

TABLE IX: Summary of the LMM analysis for the pedestrians' AV-gazing time.

Fixed effects	Est.	SE	p-value
β_0	2.607	0.247	<0.001
$\mu_{Block:ped} \oplus ped$	-1.081	0.270	<0.001
$\mu_{Block:ped} \oplus cyc$	-1.234	0.275	<0.001
$\mu_{Loc:close}$	-0.468	0.256	0.070
$\mu_{Block:ped} \oplus ped \times \mu_{Loc:close}$	0.611	0.371	0.101
$\mu_{Block:ped} \oplus cyc \times \mu_{Loc:close}$	0.236	0.373	0.528
Random effects	Var	SD	p-value
$\psi_{pair} : \psi_{player}$	1.024	1.012	<0.001
ψ_{pair}	0.000	0.000	1.000
Residual	1.032	1.016	
Model			
Observations	179		
Marginal R^2	0.1076		
Conditional R^2	0.5521		
logLik	-289.4		
AIC	596.7		
BIC	625.4		

6) *Pedestrian's AV-Gazing Time*: Table IX and Figure 12 summarize the LMM results for pedestrians' AV-gazing time, revealing significant fixed effects, particularly related to the number and role of VRU.

The baseline scenario, where pedestrians started at the farther location in the absence of the second VRU, showed an estimated AV-gaze time of 2.607 seconds. The analysis highlighted a significant reduction in AV-gaze time when

pedestrians were accompanied by a second pedestrian or cyclist, with reductions of 1.081 seconds and 1.234 seconds, respectively. The effect of proximity to the AV was not significant, with the estimated change in gaze time being -0.468 seconds for pedestrians starting closer to the AV, though this effect was only marginally significant ($p = 0.070$). Interaction effects between the VRU combination and initial location were also non-significant.

Our findings indicate that when a pedestrian is accompanied by another VRU, their AV-gazing time decreases compared to when crossing alone, aligning with the results of [17], where two pedestrians encountered an HDV. In another study focusing on AV in shared space [15], the pedestrian further from the AV showed a significant decrease in AV-gazing time compared to crossing alone, but the pedestrian closer to the AV exhibited an insignificant slight increase. Our study similarly reveals that the closer pedestrian's AV-gazing time decreases less than that of the further pedestrian. This further confirms that group dynamics may cause the pedestrian farther from the AV to spend less time focusing on it, however, the AV-gazing time changes of the pedestrian closer to the AV does not reach an agreement. We assume this inconsistency is caused by the body representation used in [15], which distracts the pedestrian's focus and only the partial body representation may not fully exhibit the social communication, hence the participant further needs more time to interpret the interaction. What's more, our study found that pedestrians closer to AV decrease their AV-gazing time when a cyclist is crossing together. This may also indicate that the existence of cyclists also distracts the pedestrian's original focus on AV, making the interaction a little bit complex.

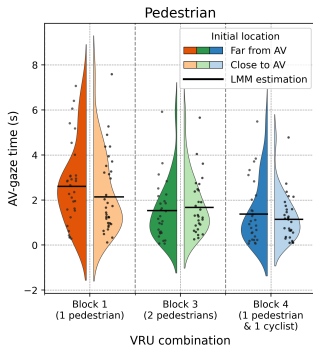


Fig. 12: The distributions of pedestrian AV-gazing time.

Overall, our AV-gazing LMM analysis not only confirms the previous findings on the impact of another VRU accompanying a pedestrian on decreasing the pedestrians' AV-gazing time but also emphasizes the distraction effect of another cyclist on the pedestrian closer to the AV. A limitation of the current study is that it only analyzed AV-gazing data, without including gazing data on other road users during the experiment. Future research should conduct a more comprehensive eye-tracking study to examine eye-gazing distribution across various objects and road users during the crossing.

D. Subjective Measures

This section analyzes subjective measures, beginning with four metrics related to the simulator assessment, followed by two crossing-related subjective metrics, and concluding with participants' feedback on the co-simulator.

1) *Simulator Sickness*: The average overall score of the Simulator Sickness Questionnaire (SSQ) is 36.18 ± 36.53 , which is slightly higher than [15]. The result in Table X presents the average scores for three sub-scales of SSQ, namely nausea, oculomotor, and disorientation. Among the sub-scales, disorientation received the highest average score of 45.24 ± 54.39 , indicating that participants experienced disorientation symptoms most intensely. This was followed by oculomotor symptoms, with a mean score of 32.97 ± 28.80 , suggesting moderate effects on visual and eye-related comfort. Nausea received the lowest average score of 19.79 ± 24.48 , showing relatively fewer symptoms related to stomach discomfort. These scores highlighted that disorientation was the most prominent symptom experienced, whereas nausea was less common among participants.

TABLE X: The average scores of the sub-scales of SSQ.

Sub-scale	SSQ score (Mean \pm Std)
Nausea	19.79 ± 24.48
Oculomotor	32.97 ± 28.80
Disorientation	45.24 ± 54.39

In terms of motion sickness, the pedestrian VR simulator was promising, as participants reported minimal motion sickness caused by it and none withdrew from the pedestrians' experiment, highlighting the system's comfort. The high acceptance of the simulator can be attributed to its implementation of free locomotion, which allowed participants to navigate freely within the room [73].

However, some participants reported slight and obvious motion sickness during cycling in VR. They suggested several enhancements to improve their VR cycling experience and to reduce the likelihood of sickness. They recommended incorporating steering functionalities to offer more control over movement and increase immersion, which aligns with similar research [50], [51]. Additionally, they suggested enhancing locomotion feedback, particularly in terms of acceleration and braking sensations, to help alleviate the sensory mismatch that can contribute to simulator sickness [51].

2) *Presence*: The presence questionnaire (PQ) results, shown in Table XI highlight the performance of our virtual reality setup compared to the benchmark, which held a double-pedestrian crossing VR experiment in a shared space, where only the heads and shoulders of the pedestrians were displayed.

The results demonstrate that our VR setup performed well. For *Involvement*, our participants averaged a score of 4.919, slightly surpassing the benchmark's score of 4.77, suggesting our design was effective in engaging users. On *Sensory fidelity*, our VR co-simulator scored 4.329, significantly outperforming the benchmark's 3.80, indicating a more realistic sensory experience in our VR setup. Regarding *Immersion*, our score of 5.522 was marginally higher than the benchmark's 5.38,

TABLE XI: Comparison of average PQ sub-scale scores.

Sub-scale	Score (Mean \pm Std)	
	Ours	Benchmark
Involvement	4.919 \pm 0.965	4.77 \pm 0.81
Sensory fidelity	4.329 \pm 1.377	3.80 \pm 0.83
Immersion	5.522 \pm 0.780	5.38 \pm 0.76
Interface quality [†]	3.217 \pm 1.658	3.96 \pm 1.10

[†] Reversed items.

showing that our environment provided a slightly more immersive experience. For *Interface quality*, a collection of reversed items, our score of 3.217 was lower than the benchmark's 3.96, meaning our interface was rated as more user-friendly and efficient.

Overall, the PQ results indicate that the VR experiment using our developed VR co-simulator offers a more effective and engaging VR experience than the previous study, especially in terms of sensory fidelity and interface quality. This can be attributed to the co-simulator's efforts to establish interactions between VRUs and AVs. Specifically, the introduction of various transport modes (i.e., pedestrian and cyclist) and the inclusion of participants' real-time behaviors in the same virtual world may have made participants feel more immersed and reactive in VR compared to earlier implementations [15].

TABLE XII: The scores of realism questionnaire.

Items in the face validity questionnaire	Score (Mean \pm Std)
The realism of the virtual environment	3.78 \pm 0.58
The realism of the virtual objects (e.g., AV)	3.75 \pm 0.84
The realism of the movement as a pedestrian	3.55 \pm 0.96
The realism of the movement as a cyclist	3.45 \pm 0.99
The realism of the environmental sound	3.58 \pm 1.06

3) *Realism*: The results in Table XII reveal variations in perceived realism across different aspects of the virtual environment in the VR realism questionnaire. Overall, the realism of the virtual environment and virtual objects (e.g., AV) received relatively higher scores, with mean ratings of 3.78 ± 0.58 and 3.75 ± 0.84 , respectively. This suggests that participants found these visual elements particularly convincing within the VR scenarios.

In contrast, the realism scores for movement abilities as a pedestrian and as a cyclist were slightly lower, with means of 3.55 ± 0.96 and 3.45 ± 0.99 , indicating room for improvement in the naturalism of movement simulation, especially in terms of walking and cycling motions. Additionally, the environmental sound realism received a score of 3.58 ± 1.06 , slightly higher than the movement scores, indicating that sound contributed positively to immersion but still has potential for enhancement. The items with lower realism scores aligned with participant feedback and suggestions provided in Section V-D7.

The average score for the questionnaire was 3.62 ± 0.58 , aligning with scores from previous studies [15], [68] investigating pedestrian road-crossing behavior in VR. These scores indicate that the VR environment effectively provided a realistic experience for participants. However, there is scope for further optimization in motion simulation and auditory effects to enhance the overall realism of the experiment.

4) *System Usability*: Table XIII presents the System Usability Scale (SUS) scores of the body tracking used in the VR experiment for pedestrians and cyclists, respectively. Regarding SUS, the pedestrian full-body tracking subsystem received a mean SUS score of 47.94 ± 14.24 , while the cyclist upper-body tracking subsystem had a score of 46.50 ± 13.56 .

According to the SUS scale, scores range from 0 to 100, with higher scores indicating greater usability. A score of 80.3 or higher is considered excellent, suggesting that users find the system highly usable and will likely recommend it to others. Scores around 68 indicate average usability, where the system performs adequately but has some areas where the user experience could be enhanced. A score of 51 or below signals a failing grade, highlighting significant usability challenges that require immediate attention to improve the system's effectiveness and user satisfaction. Therefore, the SUS scores of body tracking for pedestrians and cyclists yielded results approaching an acceptable standard, but there is a large space for improvement in future development.

TABLE XIII: The average SUS scores for two body-tracking sub-systems.

Subsystem	SUS score (Mean \pm Std)
Pedestrian full-body tracking	47.94 ± 14.24
Cyclist upper-body tracking	46.50 ± 13.56

The low SUS scores may be attributed to several factors: First, the current body tracking system is not fully optimized for participants of varying heights. It performs best for individuals around 170 cm, and for others, the tracking is automatically scaled based on the ratio between the participant's height and the avatar's height. Second, the body tracking experience is closely tied to the avatar's body representation. We currently use MetaHuman to display participants, but it is computationally intensive, particularly in rendering detailed features like hair, which may affect the overall experience. Third, we anticipate that more advanced algorithms will enhance body-tracking accuracy. Currently, we use a built-in inverse kinematic algorithm to estimate body gestures. Future versions will incorporate state-of-the-art algorithms to improve accuracy.

While participants' SUS scores indicated lower satisfaction levels and highlighted potential areas for improvement, it is important to recognize that these body-tracking systems are still in their early prototype stages. Despite the low SUS scores, the systems demonstrated significant reliability and functionality during the VR experiment. This underscores the viability of utilizing VR systems for real-time body tracking and realistic representation of pedestrians and cyclists, as opposed to relying on partial body representations [15] or simple geometric proxies [16], [18].

5) *Trust in AV*: The level of trust in AVs was measured per participant using a scale ranging from 1 to 7 [25], [70]. This scale contained questions such as "Globally, I trust the automated vehicle", "I trust the automated vehicle to have seen me", and "I trust the automated vehicle to drive safely". Table XIV presents the trust in AV scores, categorized by overall participants and further divided by gender.

TABLE XIV: The average score of trust in AV.

Group	Sample size	Trust in AV (Mean \pm Std)
Overall	40	5.01 \pm 1.11
Male	20	4.65 \pm 1.22
Female	20	5.37 \pm 0.87

The mean score was 5.01 ± 1.11 , indicating a moderate level of trust in the AV, which is slightly higher than the previous study [15] (4.42 ± 1.09). Furthermore, the T-test ($t = -2.13, p = 0.04, df = 34.4$) and Mann-Whitney U test ($U = 127.5, p = 0.049$) were conducted to evaluate gender-based differences in trust in the AV. The results indicate a statistically significant difference in trust levels between genders, with males showing slightly lower trust in the AV compared to females.

6) *Perceived Behavioral Control*: Table XV shows the average scores of both the perceived behavioral control (PBC) and perceived risk (PR) questionnaires, categorized by overall participants as well as by gender.

TABLE XV: The average scores of PBC and PR.

Group	#Sample	PBC (Mean \pm Std)	PR (Mean \pm Std)
Overall	40	2.41 \pm 1.14	5.56 \pm 1.07
Male	20	2.72 \pm 1.43	5.35 \pm 1.14
Female	20	2.10 \pm 0.64	5.78 \pm 0.96

PBC refers to an individual's belief about their ability to perform a particular behavior, according to the theory of planned behavior [74]. The PBC questionnaire comprised two items on a 7-point bipolar scale: "For me, crossing the road in this way would be ..." and "I believe I have the ability to cross the road in this way as described in this situation." The first item was rated on a scale from very easy (score 1) to very difficult (score 7), while the second item was rated from strongly agree (score 1) to strongly disagree (score 7). It is important to note that we utilized an inverted 7-point scale for PBC measurement.

These two items together resulted in an average PBC score of 2.14 ± 1.14 , which is lower than the scores recorded for individual participants interacting with an AV (3.16 ± 1.63) or an HDV (3.28 ± 1.77) in the conventional street as per [12], and for two pedestrians crossing simultaneously with an AV in shared space (2.73 ± 0.96) according to [15]. It confirms that pedestrians show a greater intention to cross in shared spaces compared to conventional road environments. Additionally, this suggests that crossing with another VRU may boost the VRU's confidence to cross when interacting with an AV. The analysis of PBC scores by gender further revealed observed differences between males and females, yet the T-test and Mann-Whitney U test results indicate these differences are not statistically significant, which aligns with the previous findings on the gender effect in [12].

Based on the version used in [15], the PR questionnaire has been updated to include three specific crossing scenarios as a pedestrian: (1) crossing the road alone, (2) crossing with another pedestrian, and (3) crossing with a cyclist. Respondents rated these items on a 7-point scale from very unsafe (score

1) to very safe (score 7).

The refined PR questionnaire resulted in an average score of 5.56 ± 1.07 , which is similar to [15] (5.09 ± 1.15). Specifically, PR scores were higher when crossing with another pedestrian (5.75 ± 1.08) or a cyclist (5.6 ± 1.06) compared to crossing alone as a pedestrian (5.35 ± 1.37). This suggests that crossing in pairs enhances the perceived safety of VRUs.

7) *Participants' Feedback*: At the end of the questionnaire, participants had the option to provide feedback and suggestions for improving the designed VR co-simulator. Twelve out of forty participants provided valid suggestions, which will be considered to enhance the design and interaction of future versions of the multi-player VR experiment. Several key areas for improvement are summarized as follows, with the number following each bold item indicating how many participants suggested improvements in that area:

- **Cyclist simulator** (3): Add steering functionality. Keeping the bike moving straight without steering options caused some participants to experience more noticeable motion sickness, which is consistent with the simulator design recommendations from previous study [50], [51], especially compared to pedestrian free locomotion movement experience [73].
- **Vehicle dynamics** (3): Make vehicle behavior more realistic and less predictable.
- **Sounds** (4): Introduce additional vehicles' sounds in the VR environment, while ensuring participants can still clearly hear instructions from the researcher.
- **Multi-player latency** (1): Minimize latency to provide a smoother VR experience.
- **Room size** (1): A larger space for movement is desired to navigate freely [73] and to enhance safety.

Participants were also asked if they would like to receive updates about the project and participate in future experiments. Encouragingly, 26 of them expressed interest in staying informed and joining future VR studies!

VI. DISCUSSION

A. Answers to Sub-Research Questions

1) *Answer to SQL simulator integration*: In this study, we initially examine the feasibility of integrating various VR road user simulators into the same VR environment. To achieve this, we utilize two existing VR road user simulators: a pedestrian VR simulator and a cyclist VR simulator. By leveraging the UE5 game engine, these simulators can be combined into a unified virtual space using the engine's built-in multi-player gaming functionality. Specifically, we choose a listen server-client architecture, where one client acts as the server during the connection. This connection architecture is currently capable of managing situations involving two VR participants. The original functionalities of two VR simulators are fully integrated into the multi-player VR co-simulator. As a result, the current VR co-simulator supports four different game modes: (1) *single-pedestrian*, (2) *single-cyclist*, (3) *double-pedestrian*, and (4) *pedestrian-cyclist mixed*. We anticipate that the same or advanced architecture can be employed to

integrate additional categories of VR road user simulators, such as driver and wheelchair simulators.

2) *Answer to SQ2 interaction development:* Following the integration of simulators, attention turns to facilitating interactions among different participants, since the initial simulators were not designed for multi-player scenarios. Previous studies have only partially illustrated the pedestrians' bodies, focusing on heads and shoulders, or even simplifying them into geometric shapes for ease. We aim to enhance this interaction by enabling participants to observe others' behaviors through real-time body movements, simulating human-to-human interactions in real-world traffic settings. This is achieved by utilizing body tracking technology to monitor key body parts of pedestrians and cyclists, such as hands, feet, and waists. An inverse kinematic algorithm in Unreal Engine 5 is then used to predict pedestrians' full-body movements based on these key body part transformations. Building on the full-body tracking of pedestrians, the cyclists' upper body tracking is developed, and the lower body is blended with predefined animations. Additionally, the MetaHuman feature is used to create high-quality digital human representations of participants. As a result, pedestrians and cyclists are depicted as realistic digital humans in VR, with their body movements tracked and replicated in real time.

3) *Answer to SQ3 data collection:* The primary objective of developing this VR co-simulator is to enable large-scale VR experiments as a viable data collection method for transportation research. Multi-player VR experiments should collect diverse data from various road users. We gather several types of data, including trajectory, body-tracking, and eye-gazing data. While the utility of these datasets has been explored in single-participant studies, they cannot fully capture the interactions between multiple road users simultaneously. By increasing the number of road users and introducing different roles, the data collected through multi-player VR experiments should provide deeper insights into the behaviors of road users and their interactions with AVs. Furthermore, by combining the post-experiment questionnaire, both objective and subjective measures can be analyzed from multiplayer VR experiments, creating a comprehensive data collection system.

4) *Answer to SQ4 Co-simulator assessment:* After implementing a VR co-simulator, it is of importance to test its effectiveness. Hence, a VR experiment was designed and conducted to assess the effectiveness and usability of the developed VR co-simulator. After the experiment, the participants were asked to fill in a questionnaire including several parts assessing the simulator sickness, realism, presence, and body-tracking usability within the VR experiment.

In terms of simulator sickness, participants rated simulator sickness similarly to the previous study, indicating that the overall experiment did not induce excessive motion sickness. However, participant feedback suggests that the bike VR simulator needs improvements in steering and acceleration/brake control. Our study received higher scores for presence and realism compared to [15], suggesting that the addition of more road users with high-quality, full-body representations and real-time tracking enhanced the immersive and realistic experience in VR. Regarding system usability for body-

tracking of pedestrians and cyclists, the results were adequate, indicating user acceptance of the subsystem. However, there is significant room for improvement since the subsystem is still a prototype. Future research plans include implementing more advanced body-tracking algorithms to provide a more accurate and flexible representation of different road users.

Overall, the VR experiment was successful, and the results presented in Section V validated the effectiveness of the VR co-simulator. The features introduced into the VR co-simulator are promising to contribute to transportation research.

5) *Answer to SQ5 VRU-AV interaction:* The VR experiment is also aimed to investigate the effects of the number of VRUs, their role, and their initial relative location on the VRUs' behaviors and interactions with the AV in shared space. Both objective metrics (i.e., negotiation time, crossing time, space gap ...) and subjective measures (i.e., trust in AV, perceived behavioral control ...) are examined to analyze the impact of VRU combinations and initial relative location.

In terms of the number and role of VRUs, the results indicate that both of them significantly influence pedestrians' negotiation time, total walking distance, AV-gazing time, and the space gap for both pedestrians and cyclists. For pedestrians, these findings are consistent with previous studies [14], [15], [25], which demonstrate that a pedestrian's movement dynamics can be influenced by neighboring pedestrians when crossing as part of a group. This understanding is extended to mixed groups of pedestrians and cyclists by our study, showing similar results. In contrast, cyclists' behaviors remained largely unchanged, except for slight adjustments in space gaps, indicating that cyclists are less likely to exhibit behavioral changes when crossing as part of a group. We interpret this as suggesting that pedestrians and cyclists may perceive the presence of other VRUs differently in terms of group association.

Regarding the impact of the relative locations of the two VRUs, it had a significant impact on pedestrians' negotiation time and space gap. The interaction effects between the relative location and VRU combination are also significant. Our study observed more cooperative crossing behaviors of VRUs, compared to the previous conclusion that when crossing the road next to each other, two pedestrians could behave differently depending on their relative standing positions [15].

Besides objective metrics, subjective measures also reveal insights into the effect of VRUs' count and role. The result reports a higher trust in AV. Additionally, participants reported greater confidence in crossing the shared space with another VRU, whether pedestrian or cyclist, than when crossing alone. The subjective self-report is consistent with the objective metrics derived from the participants' behaviors.

Overall, we confirm the influence of the number of VRUs, their role and the initial relative location on VRU-AV interaction in shared space. The observed decrease in negotiation time and AV-gazing time when pedestrians cross together suggests that mutual awareness and implicit coordination within a pair play a crucial role in making the crossing decisions. These results further underscore the importance of considering both individual and collective dynamics in studies of shared spaces, as synchronized behaviors and reduced attention to AVs may

indicate an increased sense of confidence or trust among group members when navigating complex traffic scenarios.

B. Answer to Main Research Question

The main research question of this master thesis is *How can a multi-player multi-modal road user virtual reality co-simulator be developed and tested to study the behaviors and interactions between various vulnerable road users?* To address this question, the study was conducted in two stages:

Development of the VR Co-simulator: In the first stage, we created a multi-user, multi-modal VR co-simulator that integrates pedestrian and cyclist VR simulators to address key research gaps in VR experiments, such as the absence of human-to-human interactions and challenges with scalability. Utilizing technologies like body tracking and MetaHuman, the system enables real-time interactions and detailed data collection, including trajectories, body movements, and eye-gaze behaviors, providing a foundation for future large-scale VR-based experimental studies.

VR Experiment Using the Co-simulator: In the second stage, a VR experiment was conducted using this VR co-simulator to 1) to assess the effectiveness of the developed VR co-simulator, and 2) explore how different VRU combinations (e.g. number of VRUs and role of VRUs) and VRUs' initial relative locations, affect VRUs' behaviors and their interactions with AVs. Shared space was selected as the studied road traffic scenario as it encourages more natural interactions, without explicit traffic rules, supporting the experiment's aim to study the interactions between VRUs and AV. The experiment involved 20 participant pairs acting as pedestrians and cyclists, with both objective data (e.g. trajectory, eye-gaze behavior) and subjective data (e.g. questionnaire responses) collected. The results from the VR experiment validate the effectiveness of the multi-player, multi-modal road user VR co-simulator. Additionally, the study illustrates the influence of the number of VRUs, their roles, and their initial relative locations on VRU-AV interactions in a shared space.

VII. CONCLUSION

A. Conclusion

To summarize, we successfully designed and implemented a multi-player, multi-modal VR co-simulator that incorporates both pedestrians and cyclists into the same VR space. This VR co-simulator aims to support large-scale VR experiments for comprehensive data collection in transportation research. It supports nightly features such as body tracking for pedestrians and cyclists, MetaHuman - a high-quality digital human representation and comprehensive data collection technologies such as body tracking and eye gazing data. A subsequent VR experiment was conducted to the effectiveness of the developed VR co-simulator and to investigate the interaction between VRU and AV in shared space. The assessment of the VR co-simulator effectively proved its capabilities and feasibility, in terms of simulator sickness, presence, realism, and usability. The VR experiment also confirms the effect of VRU combinations and VRUs' initial relative locations on the VRU-AV interaction in shared space.

B. Current Limitations

The co-simulator design exhibited several shortcomings and limitations during the experiment. First, the body tracking setup needs refinement to achieve more accurate participant tracking. Second, the bicycle VR simulator requires enhancements, particularly in steering control, to improve its fidelity.

The VR experiment procedure also has limitations that may influence the results. First, the lack of randomization within each block could introduce learning effects. Second, the AV consistently approached the VRUs from their right-hand side, limiting scenario variability. Introducing more randomization is necessary in future studies.

C. Future Work

Several promising research directions could enhance the VR co-simulator and expand the scope of VRU-AV interaction studies. First, incorporating a larger number of participants within the same VR scenario would allow for the examination of group or crowd behaviors. Second, including additional road users, such as drivers or wheelchair users, in the VR scenario would facilitate the investigation of more complex interactions among different road users. Lastly, the application of other extended reality technologies, such as augmented reality and mixed reality, holds promise for multi-player experiments.

APPENDIX A PARTICIPANT DEMOGRAPHICS

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TABLE XVI: Summary of Participant Demographics.

Descriptive information	Category	Number (%)
Gender	Male	20 (50.00%)
	Female	20 (50.00%)
Age group	10-19	0 (0.00%)
	20-29	34 (85.00%)
	30-39	5 (12.50%)
	40-49	0 (0.00%)
	50+	1 (2.50%)
Highest education level	High school	2 (5.00%)
	Associate degree	0 (0.00%)
	Bachelor's degree	4 (10.00%)
	Master's degree	29 (72.50%)
	Doctoral degree	5 (12.50%)
Familiarity with any computer gaming	Never	3 (7.50%)
	Seldom	9 (22.50%)
	Sometimes	12 (30.00%)
	Often	8 (20.00%)
	Very often	8 (20.00%)
Previous experience with VR	Never	6 (15.00%)
	Seldom	15 (37.50%)
	Sometimes	12 (30.00%)
	Often	3 (7.50%)
	Very often	4 (10.00%)
Familiarity with the concept of shared space	Never	14 (35.00%)
	Seldom	8 (20.00%)
	Sometimes	2 (5.00%)
	Often	9 (22.50%)
	Very often	7 (17.50%)
Previous experience with shared space	Never	17 (42.50%)
	Seldom	4 (10.00%)
	Sometimes	8 (20.00%)
	Often	5 (12.50%)
	Very often	6 (15.00%)
Familiarity with the concept of automated vehicles	Never	3 (7.50%)
	Seldom	7 (17.50%)
	Sometimes	10 (25.00%)
	Often	11 (27.50%)
	Very often	9 (22.50%)
Previous experience with automated vehicles	Never	21 (52.50%)
	Seldom	8 (20.00%)
	Sometimes	6 (15.00%)
	Often	3 (7.50%)
	Very often	2 (5.00%)

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