



Center for Advanced Multimodal Mobility Solutions and Education

Project ID: **2021 Project 06**

PEDESTRIAN BEHAVIOR AND INTERACTION WITH AUTONOMOUS VEHICLES

Final Report

by

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September 2022

ACKNOWLEDGEMENTS

This project was funded by the Center for Advanced Multimodal Mobility Solutions and Education (CAMMSE @ UNC Charlotte), one of the Tier I University Transportation Centers that were selected in this nationwide competition, by the Office of the Assistant Secretary for Research and Technology (OST-R), U.S. Department of Transportation (US DOT), under the FAST Act.

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EXECUTIVE SUMMARY

It is expected that Connected & Autonomous Vehicles (CAV) will be seen on public roads in the near future. Traditional road users & AVs will be sharing the same urban space. The expected commencement of autonomous vehicles (AVs) has triggered intense research within the transportation community in recent years. The interaction between pedestrian and autonomous vehicles are challenging due to the complexity of their interaction process. While crossing a road, a pedestrian continuously checks for oncoming vehicles. Non-motorized users often rely on eye contact, hand motions, or audible dialogue with human drivers to accomplish roadway crossings. However, while crossing an intersection with autonomous vehicles, there is no driver with whom to interact. Human interaction and communication elimination with AV technology could influence unpredictable pedestrian behavior.

Research shows that pedestrian-driver interaction at an intersection occurs with eye contact, facial expression, and hand gestures. Signs, like body movements and posture, influence pedestrian-driver communication. This implicit transaction decides who crosses the road first. The introduction of explicit communication with AV would be a big concern for traffic operations on a roadway. Therefore, mutual communication between the AV and pedestrians is important to understand pedestrian behavior. Currently, intensive research activities are being conducted on autonomous vehicle technologies; however, how an autonomous vehicle would interact with pedestrians is much less investigated. Hence, the study of autonomous vehicle interaction with pedestrians is crucial.

This study investigates how a pedestrian would understand and respond to autonomous vehicles. This study aims to learn more about the expected behavior patterns and challenges experienced by pedestrians with AV technology. In addition, there is interest in learning about pedestrians' communication and interaction with AV. Psychophysical changes will be observed while interacting with AVs in a virtual reality setting to understand pedestrian attributes while crossing the roadway with this new technology. This insight into pedestrian behavior could be helpful to in designing technology for autonomous vehicles and making improvements to pedestrian infrastructure and traffic control technology. The effectiveness of a warning system and external features in the interaction of human-driven vehicles and pedestrians can also help the development of AVs.

Chapter 1: Introduction

1.1 Problem Statement

Pedestrians prefer a constant exchange of information with the driver so that they can get a response immediately [1]. A pedestrian-based questionnaire survey reveals that they use eye contact and hand signals to anticipate when it is safe to cross. Human sensory input is mostly visual, which is about 80% of the total input, where human has an angle of vision of 170 degrees horizontally. To design a visually represented piece of information for the human, the designer needs to focus on the choice of color, the intensity, contrast, and strength of color as well as the angle of vision. [2]. On the other hand, drivers use some informal methods like signal turning, braking, and emergency light blinking. Research shows pedestrian driver interaction at a crossroads occurs with eye contact, facial expression, and hand gestures [3]. These signals, like body movements and posture, influence pedestrian-driver communication [4]. This implicit transaction decides who crosses the road first. Introducing explicit communication with AV would be a big concern for traffic operations on a roadway.

Currently, the technology for vehicles to cruise autonomously is being heavily researched, but how an autonomous vehicle interacts with pedestrians and pedestrians will interact with AV is relatively unclear. Hence, the study of pedestrian interaction with AV is indispensable. Furthermore, pedestrian behavior and their perception of vehicles in different situations can be a starting point of the investigation - to design the interaction between autonomous vehicles and pedestrians. Therefore, the following research question has been framed: *Are there significant behavioral changes in how pedestrians interact with vehicles at a crossing when a portion of the vehicles is autonomous?*

1.2 Objectives

The objective of this research focuses on the following topics. The first objective is to determine the impact of autonomous vehicles on pedestrian measures such as gap acceptance, waiting time, and acceleration rate while crossing the road. This research will compare the pedestrian behavior changes with the automation level of the vehicle. The second objective is to understand the psychophysiological (e.g., Electrodermal Activity-EDA, blood pressure, and heart rate change) changes of the pedestrians' while interacting with different automation level of the vehicle. And lastly, the third objective to propose a modified social force model to quantify the variation of pedestrian behavior with the presence of AV. This study will compare the result with different age group, gender, and income with the use of virtual reality lab.

1.3 Expected Contributions

The study will benefit the state of practice for in transportation planning and provide a better understanding of this emerging technology and the community's opinions. In addition, this study's results can enhance road safety for pedestrians at signalized and non-signalized intersections.

1.4 Report Overview

The remainder of this report is organized as follows:

- Chapter 2 is a literature review of the previous works on substantive research questions. This section briefly discusses pedestrian behavior while interacting with human-driven or autonomous vehicles.
- Chapter 3 describes in detail the methodology of this project and the data sources that were used.
- Chapter 4 looks in detail at the results of the University of Connecticut community public perception survey as a demonstration of how the general public will react when AVs on the road.
- Chapter 5 describes the modified social force model and pedestrian behavior when AVs are on the road.
- Finally, the discussion and conclusions are presented in chapter 6.

Chapter 2: Literature Review

2.1 Introduction

The advent of autonomous vehicle technology raises questions about impacts on pedestrian behavior and interactions with CAV. Eye contact between pedestrians and drivers increases the probability of the vehicle yielding to pedestrians [5]. In their naturalistic study, Nathanael et al. [6] reported that a pedestrian head turning towards a vehicle was sufficient for drivers to confidently infer the pedestrian's intention, around 52% of interaction cases were observed similarly. Mutual eye contact between driver and pedestrian was observed only in 13% of interaction cases, accompanied by explicit signaling in 2% of total cases.

Pedestrians have their intention to cross the road and engage with drivers in some interaction. As discussed above, this interaction involves exchanging cues such as gaining attention through eye gaze or gestures to indicate one's desire [7]. Human drivers can judge the pedestrian's intention and react to the situation [4]. Similarly, pedestrians can intuitively estimate drivers' intentions from the driving behavior cues or hand waving.

Pedestrians' may make incorrect crossing decisions when interacting with an AV in different ways. There could be a problem of perception or comprehension, as they might be unable to distinguish whether they are interacting with a human-driven vehicle or an AV [27]. For self-driving vehicles, it is still challenging to understand this informal language of traffic. Even if a human driver is sitting on a driving seat, communication between a pedestrian and a driver is impossible. The driver of AV may be performing a non-driving task such as reading a newspaper, so that not paying attention to the road [8]. Pedestrians will be more confused as to whom to interact with. They will be unable to differentiate between a distracted driver and a driver sitting in an AV. Furthermore, cultural differences in the informal language of road users make robotic vehicle decisions more difficult.

2.2 Intent Perception and Communication

The behavioral psychology of pedestrians is complex, influencing their crossing decisions [9], [10]. Studies show that pedestrian demographics, social, dynamic, and traffic conditions significantly impact pedestrians' crossing intentions [11]. However, pedestrians might behave more unpredictably when confronted with self-driving vehicles than conventional vehicles. Understanding pedestrians' intentions on the road are crucial for autonomous vehicle to infer their possible actions. Future vehicles' challenge is incorporating various contextual information into their pedestrian intention estimation algorithms [12]. Vice-versa, the vehicle's intent should be clear to pedestrians. Hence, another challenge is building a helpful communication mode to communicate the vehicle's intent to human road users [13]. A quasi-experiment conducted by Gueguen et al. [5] states that pedestrians stare or not stare at drivers while approaching an intersection impacts their behavior. Pedestrians are aware of the approaching vehicle, if they are automated or not, and their walking pattern changes. Some participants in this study stopped at the path after noticing an automated vehicle.

Rothenbücher et al. [14] tested their "ghost driver" platform by hiding a human driver inside a seat suit in a car labeled as an automated vehicle. They found that the Wizard-of-Oz automated vehicle did not alter pedestrians' interactions and road-crossing behavior as long as the vehicle did not behave unpredictably at pedestrian crossings and roundabouts. Participants in this study mentioned that they had lower expectations of autonomous cars than human drivers. One participant walking in front of the vehicle stated, "*The risk I took by crossing the intersection was higher than I realized because nobody is behind the wheel of the car.*" The result from this study shows that the participants remarked that they "*didn't feel very comfortable,*" "*wanted to make sure that it wasn't going to hit me,*" or "*kept an eye out while crossing.*" Furthermore, a study conducted by Rodríguez Palmeiro et al. [27] reported similar results. When pedestrians interacted with Wizard-of Oz automated vehicles where drivers were distracted by other activities or when a car was marked as self-driving, their willingness to cross did not change but altered their behavior.

2.3 Autonomous Vehicle Visual Signals Concepts

Visual Signals have been used on conventional vehicles to communicate driver intention; similarly, the automotive industry is embracing the idea that autonomous vehicles can also use visual signals to communicate their intentions. Some researchers proposed some conceptual solutions for AV and pedestrian communication, including display, light, and projector [15]. Lagstrom and Lundgren (2015) [16] worked with a video-based approach and considered LED strips in different sequences to communicate the different modes of the vehicle (for example, 'about to start: LED strips shrink down toward the center or 'about to yield: LED strips expands toward the sides'). The results indicated that the pedestrians understood the signals after only a short training. The interface replaced the informal communication of a human driver with clearer and more prompt notifications.

These features do not provide a message about the vehicle's intention defined and understood by the general public (without previous training). In 2016, using an online survey with 182 participants, Deb et al. [17] identified pedestrians' expectations for AVs' external features, considering both visual and audible features, and solicited participants' suggestions. Most respondents preferred a visual sign, such as a 'walking pedestrian sign' or a 'timer clock,' indicating the vehicle's intention to stop at a crosswalk. The respondents also recommended including audible interacting features for distracted and visually impaired pedestrians.

In a survey study, Fridman et al. [18] tested 30 design interfaces for different states of an autonomous vehicle using responses from 200 participants. The study recommended using a green 'walk' in text with a pedestrian silhouette for a safe crossing while using 'do not walk' in red and an upraised hand to stop pedestrians from crossing. However, using color alone may confuse based on different road-user perspectives. In another study, Clamann et al. [19] tested various designs for 'walk' and 'don't walk' signs. They concluded that pedestrians are more likely to base their road-crossing decisions on legacy behaviors (for example, the gap between them and the vehicle/s and the vehicle speed) rather than information presented on the external display. However, in this study, a human passenger was present in the driver's seat to control an adverse situation. The human driver's presence in an autonomous vehicle will confuse the pedestrians regarding the vehicle's control. This situation can result in more unpredictable conditions like near misses or crashes. To better understand pedestrians' perception of AV, the researchers used a validated

pedestrian simulator [28], which used Unity 3D and an HTC Vive headset. This study's validation results showed that the participants' walking speeds in the simulator matched the average pedestrian crossing rates with a human-driven vehicle. The survey responses also revealed that participants experienced a good sense of presence in the virtual environment and rated the simulator with high usability and realism points.

2.4 Autonomous Vehicles and Pedestrian Trust

Pedestrians may have misplaced trust in AVs and incorrect expectations about the behavior of AVs. For example, if a pedestrian believes that the approaching vehicle is a self-driving vehicle. They may accept a short gap believing that AVs will yield in all cases. On the other hand, pedestrians may cross with a large gap, because they do not trust the AV's capabilities, so the waiting time will increase significantly for pedestrians. Jayaraman et al. [20] used the uncertainty reduction theory (URT) to explain pedestrians' trust in an autonomous vehicle is proportional to their knowledge of it. However, the latest robotics trust researchers suggest that a user's trust in a robot is not entirely dependent on its performance [21] but on its perceived capabilities [22].

2.5 Phyco-Physiological Study of Pedestrians With AV

Despite the progress being made in the pedestrian behavior of pedestrian–AV interaction, there remain several areas that are underexplored. This research will focus on understanding the pedestrians' psychophysiological (e.g., Electrodermal Activity-EDA, blood pressure, and heart rate change) changes while interacting with AV. The psychological response to any changes in daily life is crucial. The psychology of pedestrians will be critical to adjust to this emerging technology. The researchers of the psychological domain are always keen to understand the psychological changes of a person in different situations. It is because psychological changes trigger various decision-making activities for every person. The traditional method of understanding a person's psychological process utilizes the traditional survey or self-reporting-based approaches [23]. However, self-reporting-based approaches possess disadvantages like highly subjective, interpretability issues, variability in replicability, and so on. Hence, different modes of methods are required to overcome these issues.

New technologies are gradually emerging to measure or quantify the psychological responses of a person. Electro Dermal Activity (EDA) is one of them. The EDA is the electrical response of human skin, which is directly related to the sympathetic nervous system of the human body. Hence, a person's psychological changes are correlated with dermal activity [24]. The EDA response data is collected from an EDA sensor, which is often a watch-like device wearied on the hand. This device can record various psychophysiological parameters of its users, which includes EDA, skin temperature (using infrared thermopile), movement of the hand (using 3D accelerometer), and Blood Volume Pulse (using Photo Platyasma Graph (PPG) sensor) [25].

Chapter 3: Research Methodology

3.1 Introduction

This study aims to recognize how a pedestrian understands and measures the response to autonomous vehicles. Pedestrians and other non-motorized users will have to rely on the new technology to understand vehicle intention. This insight into pedestrian behavior could help design the interface for autonomous vehicles. In addition, the effectiveness of a warning system and external features in the interaction of human-driven vehicles and pedestrians can also help inform intersection design for vehicle fleets containing AVs.

3.2 Overall Study Design

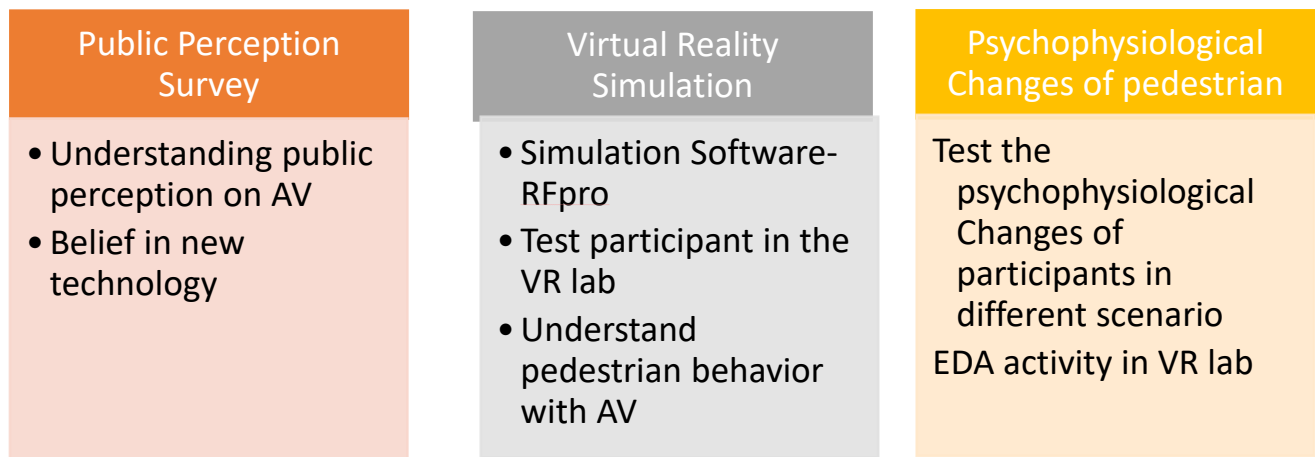


Figure 3-1: Study Design.

This study will be conducted in three phases. In the first phase, the study will complete a questionnaire survey to understand the public perception and pedestrians' expectations of AV technology. The questionnaire survey is developed and deployed via Qualtrics. The 2nd phase of the project involves VR data collection. Finally, phase 3 of this project involves psychophysiological data collection of the pedestrian while interacting with AV in a virtual reality simulation lab to understand pedestrian behavior in the presence of autonomous vehicles.

The study has several categorical independent variables (Intersection type, vehicle type, automation level) and three objective measures as dependent variables. The objective measures include the minimum gap between vehicle and participant, waiting time, and pedestrian walking speed. In addition, the trials included various scenarios for VR study in RFPro.

3.3 Data Collection

3.3.1 Public Perception Data Collection via Questionnaire Survey

A questionnaire survey was administered to understand the knowledge and public perception with autonomous vehicle (AV) while crossing an intersection as a pedestrian. This study will help

discover more about the expected behavior patterns and challenges experienced by pedestrians with AV technology. From this stated preference survey, we are interested to know about the public perception, challenges, and expectations of AV technology. Survey questions cover knowledge about AV, faith in this technology, transportation preference, and demographic information. The survey questions are in multiple-choice and short answer forms.

3.3.2 Pedestrian Behavior Data Collection in Virtual Reality Simulation

A pedestrian simulator using an RFpro environment and virtual reality headset (available through the Connecticut Transportation Institute's (CTI) VR and Simulation Lab) is utilized in this study. RFpro is a low-cost and easily navigated simulator capable of providing free-movement opportunities for the participants.

RFpro contains several features, including dynamic lighting, spatial audio, physics modeling, and scripting support, to enable the interactions between the objects in the virtual environment. This interface can be used to design a traffic environment like the real world, which could be visually and audibly experienced by wearing a VR headset and walking around a large room free of obstacles. In addition, the head-mounted device provides stereoscopic images, consisting of two images of the same object taken at slightly different angles that are viewed together, creating an improved immersion experience.

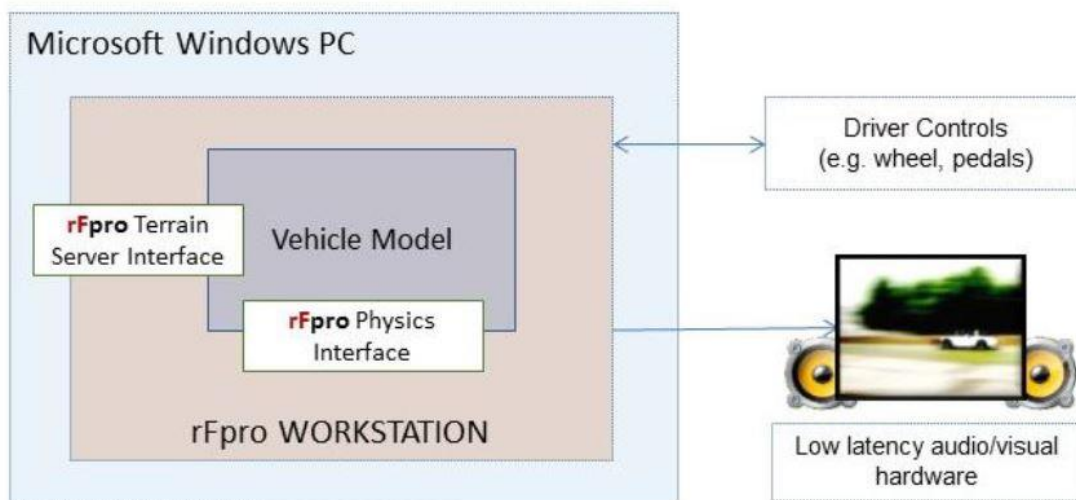


Figure 3-2 An Example of a Generic RFpro Workstation instance.

3.3.3 EDA Data Collection

As stated before, this study will investigate the participants' psychophysiological responses in the virtual environment while interacting with AV. The EDA (Electro Dermal Activity) sensor will measure the psychophysiological changes. The EDA sensor uses skin conductance to record stress levels. The EDA sensor uses a small electrical charge to measure the amount of skin conductivity an individual has on their finger. The greater the control, the greater the skin conductance. The EDA sensor will be synced with the simulation environment in RFpro to collect VR and stress data simultaneously. The participant is expected to wear a VR headset and an EDA sensor on two

fingers in one hand. Shimmer3 GSR + Unit SR 48- 3- 0 and Shimmer3 EXG Unit SR 47- 4- 0, these two devices from imotion will be used to collect the EDA data.

3.4 Participant Selection

A total of 40 participants will be recruited from the University of Connecticut and the surrounding community. All participants should be fluent in English. In addition, they need to have a standard or full-color vision. Participants are expected to walk at an average pace and should be able to walk for a speed of 1.5 miles per hour. We hope to have the user age range between 18-35 with minimum experience with virtual reality. Participants could move around all the different areas, including the sidewalks, the road lanes, and the wait areas. Participants will encounter AVs while crossing in either direction.

3.5 Statistical Analyses

The data will be analyzed using Rstudio for the objective measures (minimum gap between vehicle and participant, waiting time, and pedestrian walking speed). Results for objective measures are expected to report as means. Two types of analysis will be done for this study. The first one will be hypothesis testing to compare the effect of objective measures in different scenarios. The second one will be observing the impact of significant variables on the dependent variable and finding how strong the relationship is between two or more independent variables and one dependent variable.

3.5.1 Hypothesis Testing

Statistical inference aims to conclude a population based on data obtained from a population sample. Hypothesis testing is used to evaluate the strength of evidence from the sample and provides a framework for making determinations related to the population. In addition, it provides a method for understanding how reliably one can extrapolate experimental findings in a sample under study to the larger population from which the sample is drawn. The researcher formulates a specific hypothesis, evaluates data from the sample, and uses these data to decide whether they support the hypothesis.

The hypothesis for the experiments are stated below:

Hypothesis 1: The walking speed of pedestrians will be higher for AV compared to HDV

Hypothesis 2: The waiting time of pedestrians will be reduced for AV compared to HDV

Hypothesis 3: The gap acceptance of pedestrians will be reduced for AV compared to HDV

Hypothesis 4: The walking speed of male pedestrians will be lower compared to female pedestrians when interacting with AV

Hypothesis 5: We hypothesize that dermal response will be higher for the first half of the crossing compared with the second half of the crossing since AV will be near the pedestrian in the first half of the crossing.

Hypothesis 6: The dermal responses will be higher if the knowledge about AV is less and vice versa.

Hypothesis 7: The participant's blood pressure will be higher while interacting with AV than HDV.

Hypothesis 8: The participant's heart rate will be higher while interacting with AV than HDV.

We will perform a Z test for our analysis.

3.6 Anticipated Results

This study is expected to identify factors influencing pedestrian behavior when interacting with AV. The study of the VR environment is expected to determine the influence of AV on pedestrian behavior. These AV interactions will provide transportation authority insight into potential safety issues associated with pedestrian-AV interactions, ideas for intersection design to mitigate these issues, and an increased understanding of effective pedestrian-AV communication methods. The study is expected to determine the influence of AV on pedestrian emotion and anxiety. These AV interactions will provide transportation authority insight into potential AV adjustment and acceptance. Finally, the outputs from this study will provide visions into the pedestrians' way of thinking about AV

Chapter 4: Public Perceptions of Autonomous Vehicles Based on Survey

4.1 Introduction

Social acceptance is the primary key to the success of any new technology. It is found in a study that some people cannot trust machines (ScienceDaily, 2019) [29]. This subsection sheds light on the public perception of the safety of AVs and the level of trust in AVs. In a different survey, more than four out of five respondents ranked safety as the most important concern resulting from the emergence of AVs [30]. Howard and Dai (2014) [31] concluded that safety and liability concerns play a critical role in adopting AVs.

People worldwide and throughout the years have expressed a high safety concern. Schoettle and Sivak's (2014) [32] survey found that 92% of respondents in the US, UK, and Australia were highly concerned about the safety of the AV in bad weather and pedestrian safety. Casley et al. (2013) [30] surveyed in the US with 467 respondents to understand how public acceptance of AVs is affected. Results show that Respondents are very concerned about the safety aspects of the AV system. According to the survey, 74% of respondents believe AVs are prone to malfunction, 57% are concerned about the system's inability to sense its surroundings, 52% are concerned about programming issues, and 50% are concerned about poor control of the system, only 6.9% have no concerns about AVs. A survey by Schoettle and Sivak (2015) [33] found that 69% of respondents were highly concerned about the safety of the AV system in the US. Kyriakidis et al. (2015) survey, which received responses from 109 countries, also found that 76% of respondents are highly concerned about AV system safety [34].

Another survey conducted by Zmud et al. (2016) [35] in Austin found that 41% of respondents won't consider AVs due to a lack of trust in the technology, 24% due to safety concerns, and 22% due to the high price. A survey by Bansal and Kockelman (2016) [36] related to respondents' perceptions about AVs and safety showed mixed results. While around one out of five respondents indicated that they would be liable if an accident were to occur, some participants agreed that automation has great potential to decrease the occurrence of accidents. Even in a survey in Australia, 68% of the respondents are highly concerned about the safety of AV systems [37]. Rezaei and Caulfeld (2020) [38] found that people weren't likely to believe in the safety and security of AVs. Among the respondents, 44% do not believe AVs are safer than normal human drivers, while 25% do. Additionally, 66% of respondents said they would not feel safe if the driver was not at the steering wheel.

Thus, the safety of AVs should be the utmost priority. Vehicles that are not safe are significantly less desirable, regardless of their benefits. The perceived safety will sway AV buyers' opinions, or rather the perceived lack of safety, of these vehicles. Therefore, AV manufacturers must emphasize their safety and prove to the public that operating an autonomous vehicle is not risky. When Sinko et al. (2017) [39] compared their survey results with those of Schoettle and Sivak (2014) [32], they showed that public acceptance did not increase with time. People became more pessimistic about AVs in 2017, with an average acceptance of 3.3 out of 5 as opposed to 3.6–4.3 out of 5 in 2014.

4.2 Methodology Questionnaire Survey Data Analysis

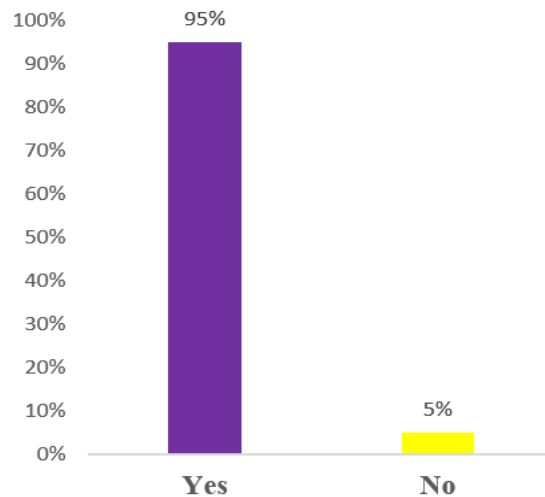
4.2.1 Data Preparation

The survey instrument included questions on demographics, vehicle ownership, comfort with automation, and willingness to use a self-driving vehicle under different conditions. The survey was constructed in Qualtrics. The participants were recruited using online posts and through an email to the UConn community. The survey was open between June 15 – August 30, 2022. Participants were told that the survey would take 15- 20 minutes and the participation was voluntary for completing the survey. In total, 85 individuals completed the survey. Most participants (more than 30) were female to the survey, followed by male participants (more than 25). Some of them were other, and a few declined to answer. Most of the participants had an age range of 55-74; followed by 35-54 years of age range and then followed by 25-34 years of age range and lastly, 18-24 years of age range. However, a few of them declined to answer.

4.2.2 Data Description

Awareness about AV

Awareness about AV was asked using the question, "Have you heard of autonomous and self-driving vehicles before participating in this survey?". The analysis sample is summarized in Figure 3 (Left). The result shows that around 95% of participants heard about AV before taking this survey. Figure 3 (Right) shows the knowledge base of participants for AV. The bar chart shows that the participants are somehow knowledgeable about AV technology. A few of them were experts in AV, more than 30 participants have done some research on AV or at least saw some video material on AV, and a similar number of participants heard about AV. Most participants (more than 50) do not have a vehicle with any level of automation. But the participants mentioned (more than 45) they had driven a vehicle with different levels of automation.



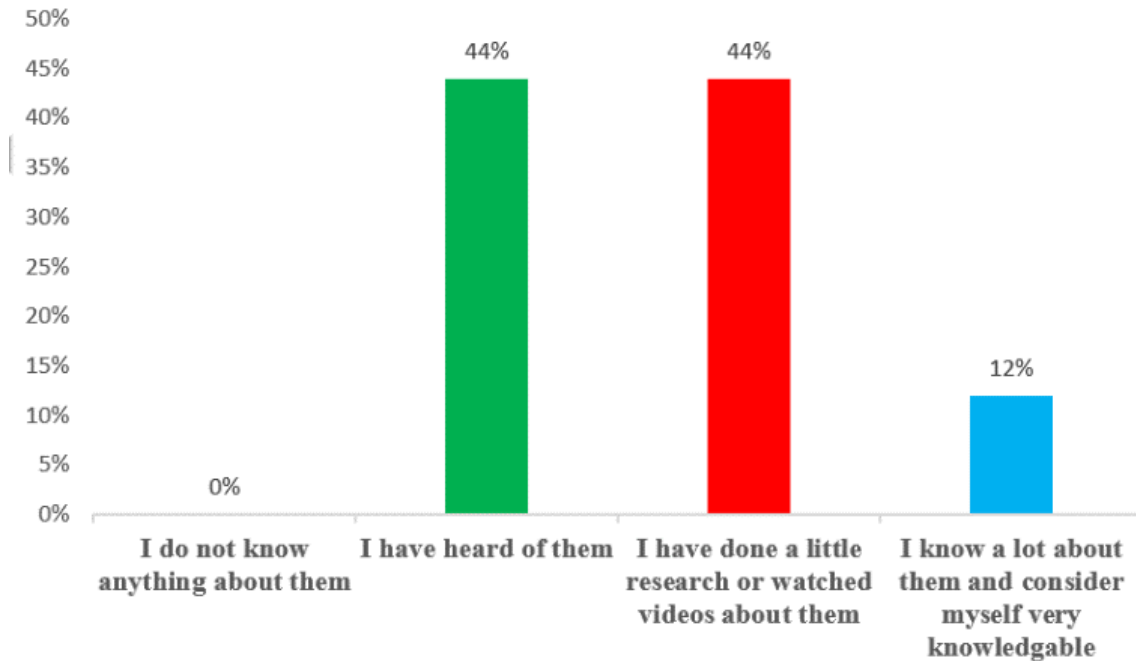


Figure 4-1 Awareness and Knowledge about AV.

Automation Preferences

Consumer preferences and level of comfort regarding various levels of automation were assessed in this survey. We had several questions related to the pedestrian. Three questions were asked about the commuting status of the participants. The results show that 90.91% of participants prefer walking in a pedestrian-friendly environment (Figure 4- Left). Around 88% of the participants do not ride the bus. Car users are prominent in our sample base; 90% of participants use cars regularly. We had some questions related to trust in AV. Survey participants were asked three questions about their preference for using AV technology. The result shows that 85% of participants declined or were unsure about riding a vehicle without driver control (Figure 4- right). Again, participants were asked if a free ride is offered in an AV-driven ride share service and whether they will avail of that ride share. The response shows that 42% do not want to use the AV-driven ride-share service. Also, in the last asked question, it is seen that most of the participants do not want to buy an AV if even it is within their budget limit.

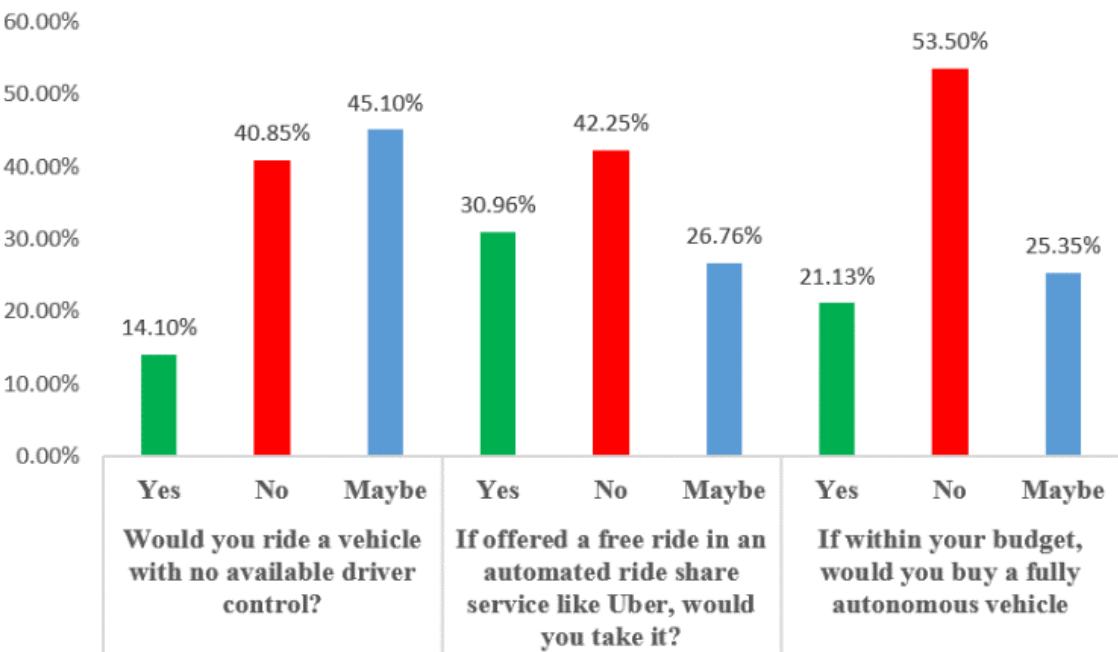
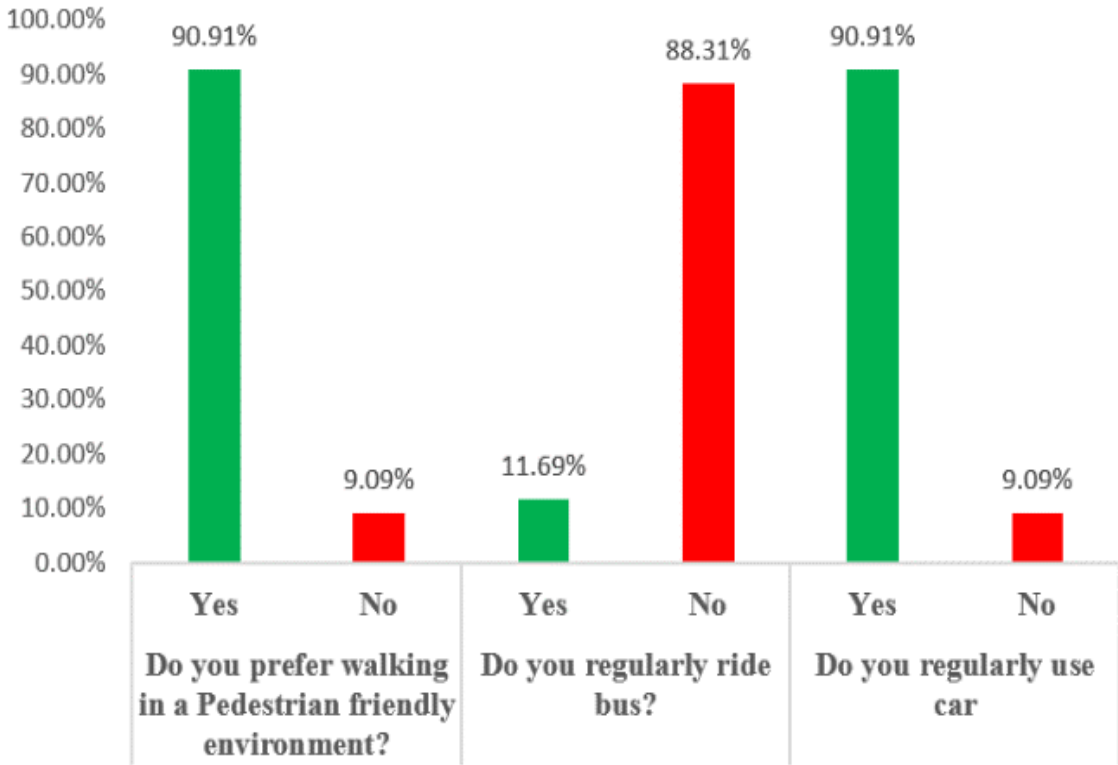


Figure 4-2 Trust perception about AV.

Pedestrian Behavior

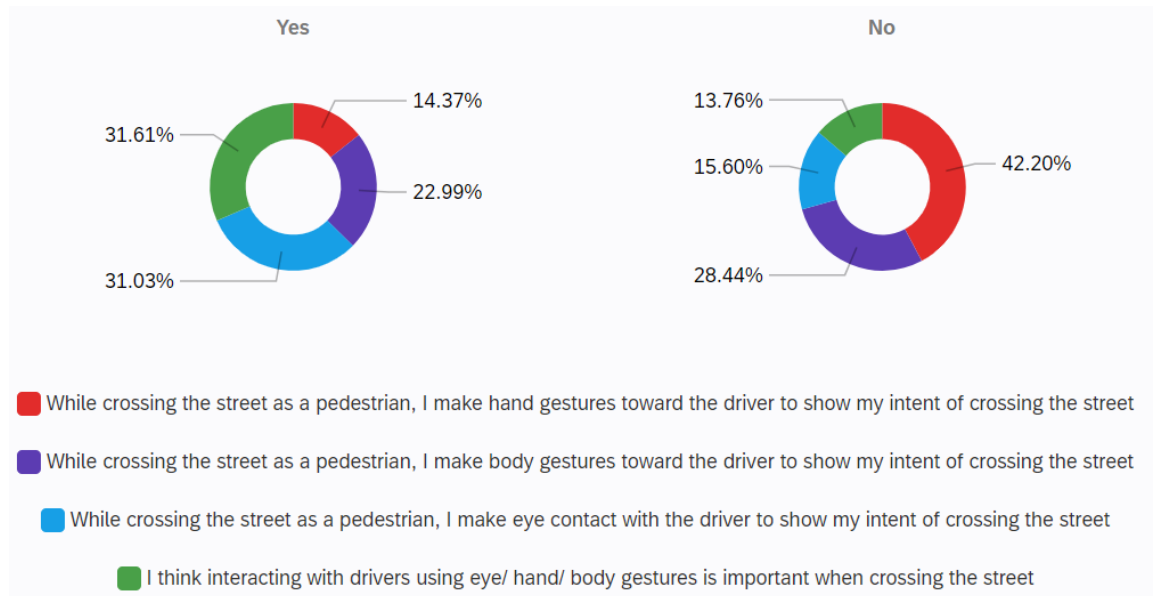


Figure 4-3 Pedestrian Behavior.

Pedestrian walking behavior also assessed with this survey. Four questions were asked about pedestrian walking behavior. From the result, it is seen that most of the participants do not use any hand gestures while crossing the road. However, a considerable number of participants mentioned (Figure 5), they use the body gesture while crossing the road. Most of the participants make eye contact with the driver while crossing the street. Most participants think eye contact/body or hand gesture is meaningful while crossing the road.

In this survey, an equal number of participants provide their opinion that they will be or will not be able to recognize a vehicle operating as driverless or not (Figure 6). Most participants answered 'no' to the question 'pedestrians do not need to communicate intentions to cross the roadway with AV on the road. In the last question, it is seen that most of the participants think that driverless vehicles will cause a safety issue for pedestrians.

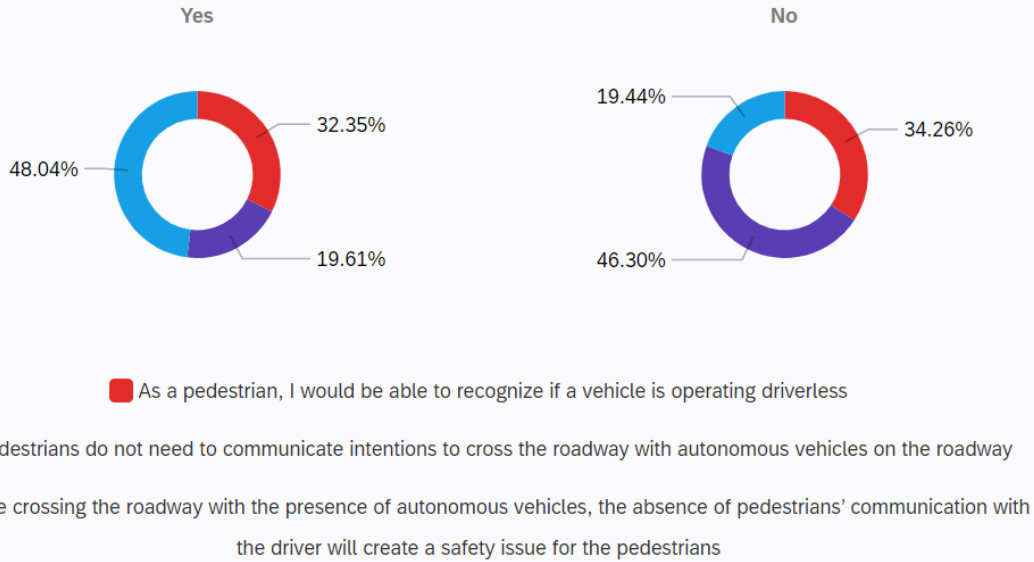
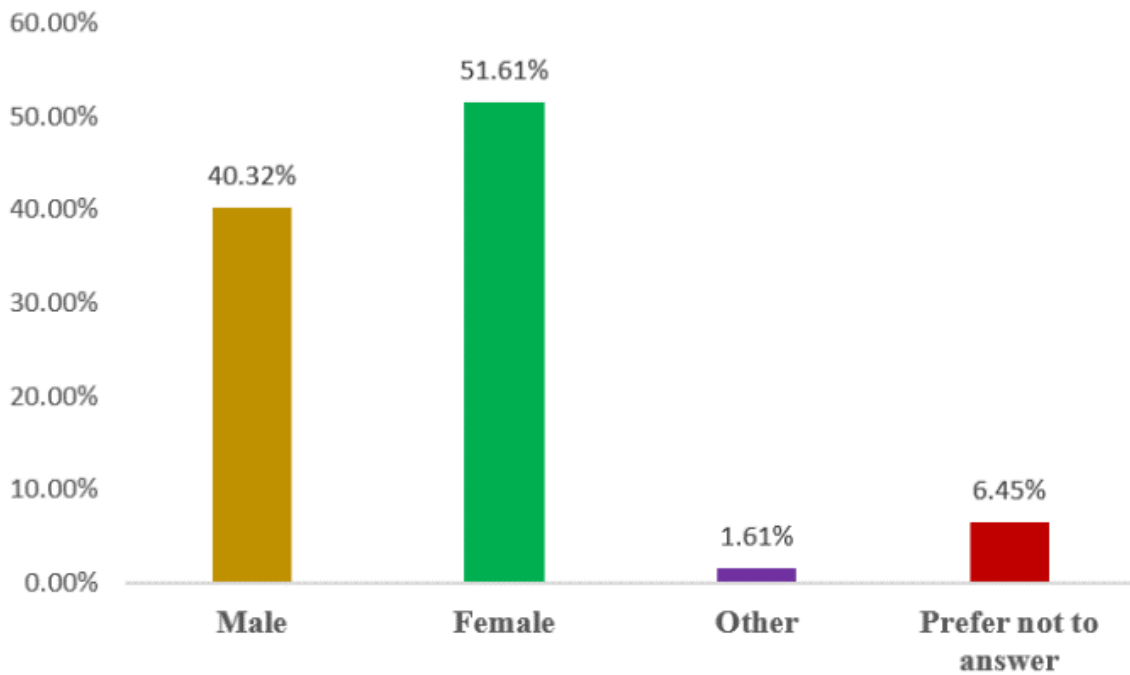


Figure 4-4 Trust of AV as a Pedestrian.

Distribution of Socio-Economic and Demographic Characteristics



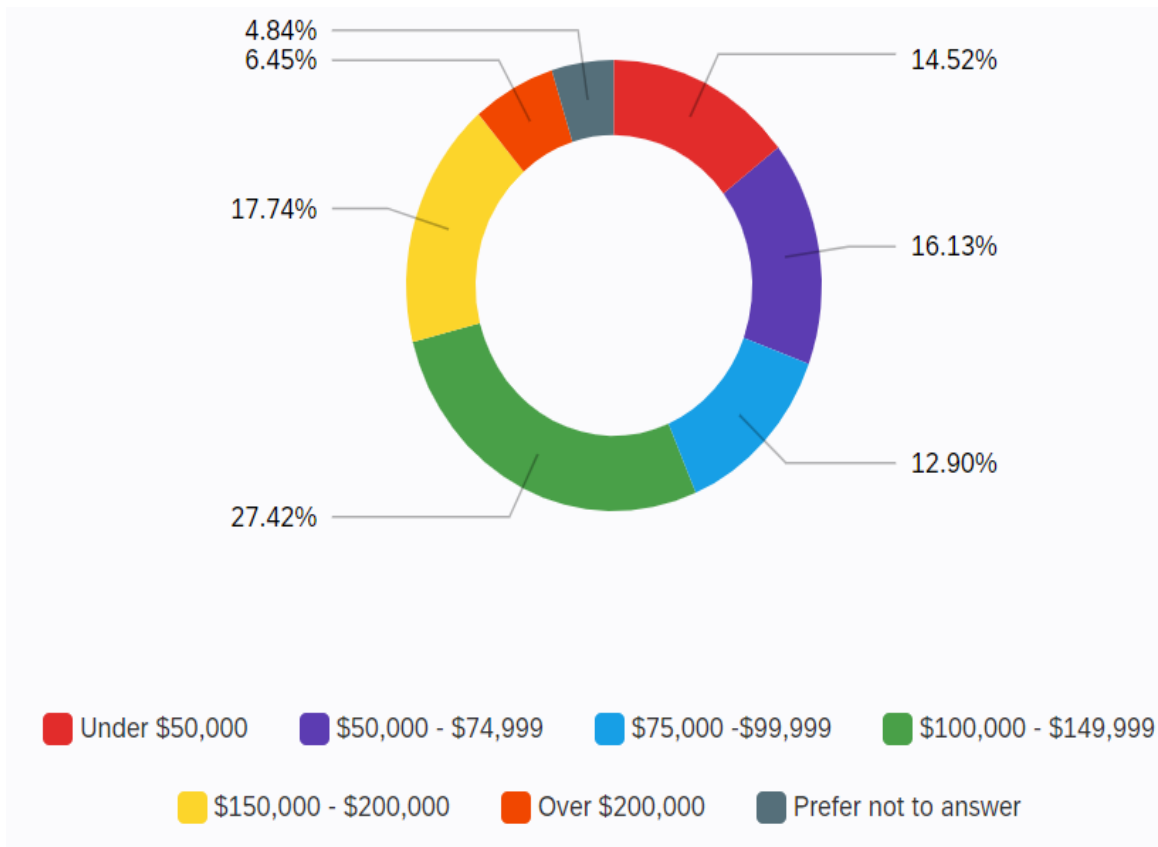


Figure 4-5 Distribution of household income of Survey Participants.

Socio- economic and demographic characteristics related questions were added to this survey. We had 51% female participants and around 40% male participants. We had a diverse range of household income in our sample. The results show that 14.5% of participants have a household income of less than \$50k (Figure 4- Right). Around 27% of the participants have an annual income of \$100k. Our survey shows that Car owners are prominent in our sample base (Figure 8); 31% of participants have at least one vehicle. The result shows that around 21% of participants have more than two vehicles, and 45% of participants have at least two in their household.

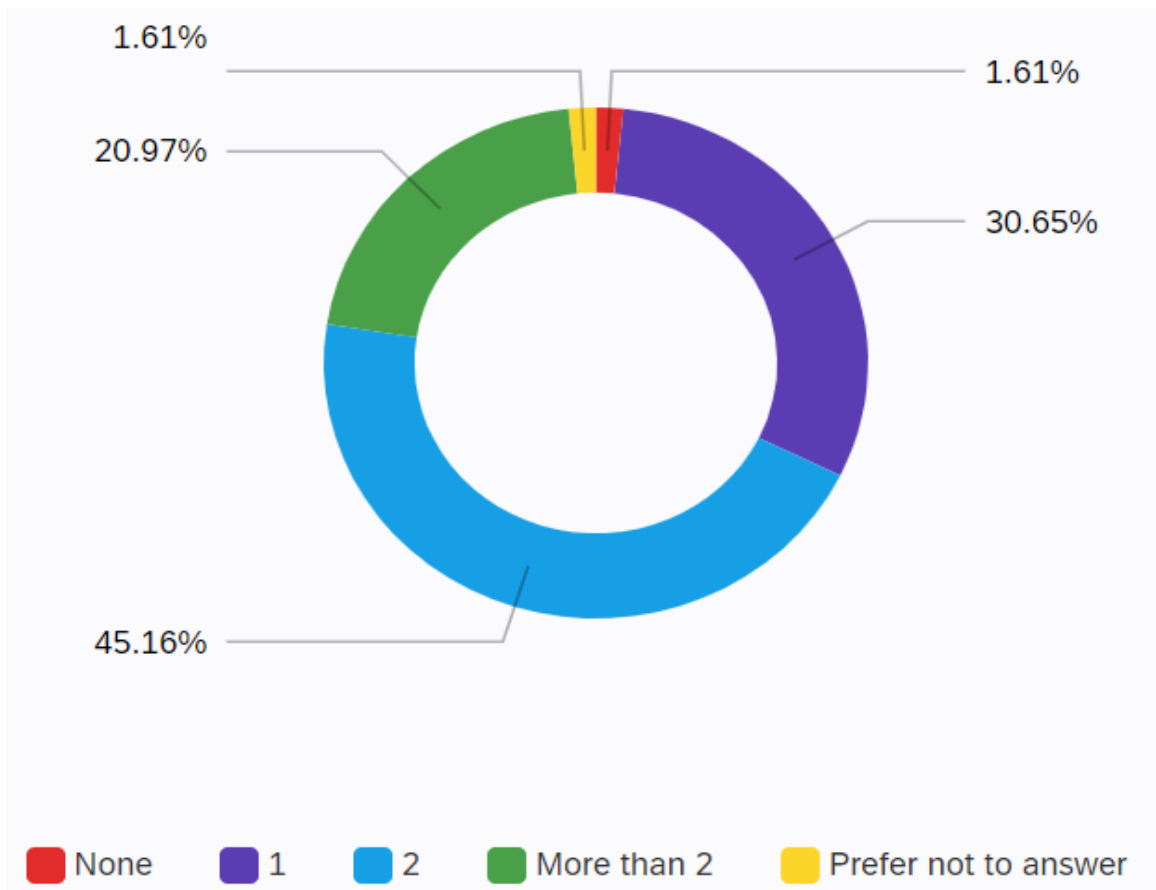


Figure 4-6 Distribution of Vehicle Ownership Among Survey Participants.

4.3 Summary

Realistic and accurate evaluations of the potential influences of AVs on transportation systems and the environment can only be achieved based on an adequate understanding of the market penetration and customers' preferences for various AV technologies and services. In addition, individuals' interests and perceptions of AVs have not changed significantly over the years. Nonetheless, public perception of AVs still represents an obstacle to their acceptance. People are generally concerned, and eventual fatal crashes that can happen over the years may cause overreaction and increase fear. Consumers are seeking assurance that self-driving features will be at least as safe as they feel with human-driven vehicles. These results suggest that consumers are hesitant about the performance of self-driving features. In addition, results indicated they were most comfortable with forms of automation in which they remained in control over those that placed the vehicle in control. A diverging trend is observed in the participants' comfort zone with full self-driving automation.

Surveys indicate that older people are the most pessimistic about AVs, contradicting the theory that older people will benefit more from them. This reluctance toward AV hasn't changed much over the years. This will remain the same until the knowledge gap is filled. Based on the survey results, Young, well-educated male workers in wealthy households are more likely to be the early

adopters of AVs, given their more vital interest and being less concerned regarding AV technology than other population segments. The survey indicates that only a small number of people are willing to pay more for AVs. The attitudes of males toward AVs are more optimistic than those of females. Similarly, those with higher levels of education are more positive than those with lower levels of education. It is also found that before experience with AVs and public acceptance of AVs are significantly correlated.

Chapter 5: Social Force Model (SFM) For the Pedestrian Behavior with Autonomous Vehicle (AV)

5.1 Introduction

Walking is a healthy, environmentally friendly mode of transportation. It constitutes the first and last part of almost any trip, regardless of what mode of transportation the user will choose later. Thus, pedestrian behavioral analysis is crucial for transportation safety and transportation planning. For example, when designing for urban roadway characteristics such as signalized or un-signalized crosswalks, or public transport stations with varying volumes of pedestrian flow, predicting the changes in the traffic conditions due to the presence of pedestrians is an important aspect of planning. To make these predictions, planners and engineers need accurate, quantitative models of pedestrian traffic.

There are various pedestrian dynamics models (PDM) available, such as the gradient navigation model by Dietrich and Koster [41]; the optimal step model by Seitz and Koster [42]; Nakayama et al.'s [43] optimal velocity model, Social Force Model (SFM) by Helbing and Molnar [44], etc. Among all these models, SFM is a widely adopted model. However, traditional SFM is not intended to understand the behavior of pedestrians in the crosswalk. Zeng et al. [45] modified the SFM to understand pedestrian behavior at a crosswalk where only human-driven vehicles are in the signalized crosswalk. However, the pedestrian's behavior in a signalized crosswalk where driverless AVs are on the road remains unexplored. Hence, this paper modifies the SFM to model pedestrian behavior in a signalized crosswalk where AVs replace all human-driven vehicles on the road.

There are two types of pedestrian stream models: macroscopic and microscopic [46, 47]. One famous microscopic pedestrian simulation model is the Social Force Model (SFM) (2000), developed in 1995 by Helbing, D., & Molnar, P [44]. The SFM captures the motion of each pedestrian using Newtonian dynamics. The basic assumption of the social force model is that danger will lead a pedestrian to act irrationally unless there is a presence of a strong positive social influence. A pedestrian is driven by inner desire, reflected by a novel concept, "desired velocity," to move to the exits as fast as possible. For example, pedestrians push each other while evacuating from a threat or perceived danger. This force is referred to as, Driving Force. During an evacuation, an individual is also affected by other individuals and their environment (such as walls and door locations). This can be viewed as a repulsive force exerted by other individuals or their physical environment. In different research sectors, researchers have modified the original SFM so that the individual movement of pedestrians can be more realistic for their respective fields. For example, Qu et al. [48] describe a modified social force model to simulate the detouring behavior of pedestrians. Kang et al. [49] show the crowd evacuation scenario using a modified social force model in a shipwreck simulation. Li et al. [50] show an advanced social force model to simulate pedestrian behavior while pedestrians aim to avoid collision. Yang et al. [51] demonstrate a modified social force model to predict crowd behavior in a corridor of a public building.

5.2 The Social Force Model for the AVs

This study will propose an adapted version of the SFM based on interactions at a signalized crosswalk. Crosswalks are the primary conflict point for pedestrians and vehicles and significantly impact pedestrian behaviors. Zeng et al. (2014) [24] mentioned one additional repulsive force of the pedestrian in a signalized crosswalk in their research, which is the repulsive or attractive force from crosswalk boundary F_c .

The AV- pedestrian interaction literature indicates that the no-driver phenomenon of the AV creates panic characteristics among pedestrians since there is no one to interact with (Rothenbücher et al., 2016 [14]). In this research, a new repulsive force, $F_{rep(av)}^{\alpha z}$ is introduced, originating from the fully automated AV interaction with pedestrians. Here the symbol z indicates an AV, and the symbol α shows a pedestrian. The other three forces are taken from the original Social Force Model: the driving force toward the destination F_p , pedestrian-related repulsive force, $F_{rep}^{\alpha\beta}$ where α and β indicates two different pedestrians, an attractive force due to different attraction in the surrounding, $F_{at}^{\alpha i}$, where the symbol i indicates a point of attraction. The resulting force, $F_a^{AV}(t)$ can be expressed by the following Equation 1.

$$F_a^{AV}(t) = F_p + F_c + F_{repv}^{\alpha\beta} + F_{at}^{\alpha i} + F_{rep(av)}^{\alpha z}$$

Hence, the presence of AV in a signalized crosswalk may create the above-mentioned five forces for pedestrians to interrupt their walking towards their destination. Since the driving force towards the destination F_p , pedestrian-related repulsive force, $F_{rep}^{\alpha\beta}$, an attractive force due to different attractions in the surrounding, $F_{at}^{\alpha i}$ is a part of the original social force model (Helbing & Molnar, 1995) [44]; the other two forces will be discussed in this section.

5.2.1 The Force from The Crosswalk Boundary

Generally, pedestrians keep moving/ walking inside the boundary of the crosswalk. In figure 9 (left), which is adapted from Zeng et al. (2014) [45], it is assumed that when there is a velocity component \vec{v}_α^x towards the crosswalk boundary, a repulsive force $\vec{F}_{B\alpha}^r$ will be generated.

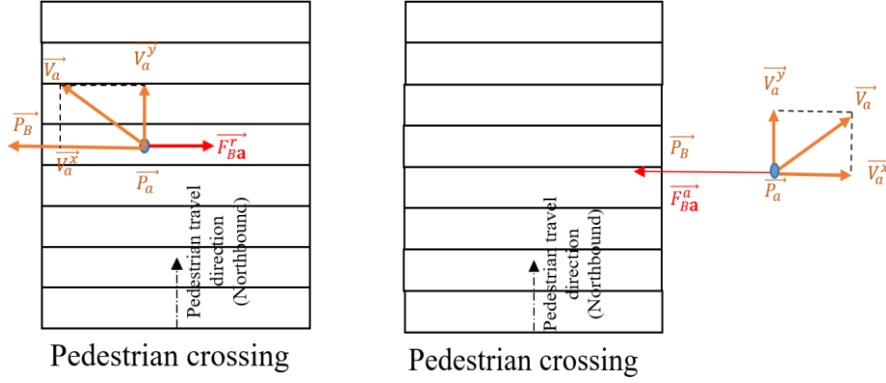


Figure 5-1 Repulsive and attractive forces from crosswalk boundary

The repulsive force makes the pedestrian retain a certain distance from the boundary. However, when the pedestrian density increases to some extent, some pedestrians may walk outside the crosswalk to avoid serious conflicts with other pedestrians in his/ her pathway. However, most of them will move back to the crosswalk once the conflict becomes less interactive. Thus, as shown in Figure 9 (right), it is assumed that an attractive force $\overrightarrow{F_{Ba}^a}$ will attract back those pedestrians outside the crosswalk. The social force from crosswalk boundary $\overrightarrow{F_c}$ can be presented by Eq. (2,3).

$$\overrightarrow{F_c} =: \begin{cases} \overrightarrow{F_{B\alpha}^r} = A_B^r \exp\left(-B_B^r \left|\overrightarrow{P_\alpha} - \overrightarrow{P_B}\right|\right) \overrightarrow{n_{B\alpha}}, & \text{if ped } \alpha \text{ inside the crosswalk} \\ \overrightarrow{F_{B\alpha}^a} = A_B^a \exp\left(-B_B^a \left|\overrightarrow{P_\alpha} - \overrightarrow{P_B}\right|\right) \overrightarrow{n_{\alpha B}}, & \text{otherwise} \end{cases}$$

Here, $(\overrightarrow{P_B})$ is the perpendicular foot-point of pedestrian α on the nearest crosswalk boundary, $(\overrightarrow{n_{B\alpha}})$ is the normalized vector pointing from boundary to pedestrian α , $(\overrightarrow{n_{\alpha B}})$ is the normalized vector pointing from pedestrian α to the crosswalk boundary. A_B^r , B_B^r , A_B^a , B_B^a are strength coefficients to be estimated.

5.2.2 Repulsive Force from AV vehicle

AVs without any external communication features are a new concept to pedestrians. Based on the previous work, it is expected a self-driving vehicle is supposed to create a repulsive panic force for the pedestrians in a crosswalk $F_{rep(av)}^{\alpha z}$. Figure 10 illustrates the repulsive force due to AV in a signalized crosswalk. It is assumed that an AV will have a circular Force field where a pedestrian will be hesitant to enter the force field. Here, $\overrightarrow{r_{\alpha z}}$ is the distance between the pedestrian $(\overrightarrow{r_\alpha})$, α and the nearest point of the circumference to the circular AV force-field $(\overrightarrow{r_z})$, the radius of the AV force-field $\overrightarrow{r_t}$, $\overrightarrow{V_\alpha}$ is the pedestrian velocity of the pedestrian, which has x and y components.

The following Equation 3 formulates the repulsive force

$$F_{rep(av)}^{\alpha z}(\overrightarrow{r_{\alpha z}}) := -\nabla \overrightarrow{r_{\alpha z}} K_{\alpha z}(\|\overrightarrow{r_{\alpha z}}\|)$$

Here, $K_{\alpha Z}(\|\vec{r}_{\alpha Z}\|)$ is the repulsive potential, and $\nabla \vec{r}_{\alpha Z}$ is the divergent behavior of the pedestrian as opposed to the location of the AV.

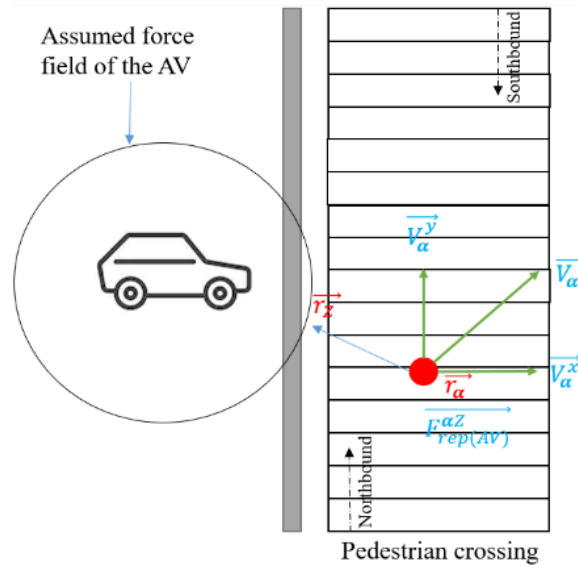


Figure 5-2 Repulsive Force of the pedestrian due to AV in a signalized crosswalk.

5.3 Model Calibration Parameters

All of the forces are adapted from Helbing and Molnar (1995) [44] and Zeng et al. (2014) [45], except the repulsive force due to AV $[F_{rep(av)}^{\alpha Z}(\vec{r}_{\alpha Z})]$. For the personal desire-related driving force $[F_p(\vec{v}_a, v_a^0 \vec{e}_a)]$, the measurable parameters are the actual velocity \vec{v}_a , The maximum allowable velocity of the road \vec{v}_{max} for pedestrians, the Dimension of the crosswalk (L*W); L stands for the length of the crosswalk, and W is the width of the crosswalk, the diameter of the personal space-related sphere of each pedestrian (D_α) to avoid collision among pedestrians, the relaxation parameter (τ_a) is a complex parameter to measure; hence, we can use a literature-based estimation for this parameter, which is $\tau_a=0.5s$ (Helbing and Molnar, 1995) [44].

The measurable parameters for repulsive force due to pedestrians $[F_{rep}^{\alpha\beta}(\vec{e}_a, \vec{r}_\alpha - \vec{r}_\beta)]$ are the following; diameter of the personal space-related sphere of each pedestrian (D_α) to avoid Collision among pedestrians, time to prevent Collision and back in track of each pedestrian while confronting (δt), the Position of each pedestrian ($\vec{r}_{\alpha 1}, \vec{r}_{\alpha 2}, \dots, \vec{r}_{\alpha n}$). Here, repulsive potential due to pedestrian $V_{\alpha\beta}$ is a non-measurable parameter; we can utilize a literature-based estimation for this parameter, which is $V_{\alpha\beta}^0 = 2.1 \text{ m}^2\text{s}^{-2}$, where $V_{\alpha\beta} = V_{\alpha\beta}^0 \exp(-b/D_\alpha)$; here, b is the minor axis of the ellipse described in the original SFM (Helbing and Molnar, 1995) [44].

For the attraction force of the pedestrian $[F_{at}^{\alpha i}(\vec{e}_a, \vec{r}_\alpha - \vec{r}_i, t)]$ the measurable parameters are the Position of the attraction (\vec{r}_i), Position of the pedestrian (\vec{r}_α), time to reach the attraction point (t_i), Attraction potential $W_{\alpha i}$ is a non-measurable quantity; in literature, the estimated value for $W_{\alpha i}$ is 0.05 (Zeng et al., 2014) [45].

Measurable parameters for force from crosswalk boundary (\vec{F}_c) for the pedestrians are the Dimension of the crosswalk ($L*W$), the Position of the pedestrian (\vec{P}_α); the adjacent perpendicular Position of the crosswalk (\vec{P}_B), The non-measurable strength coefficients are estimated as $A_B^r=0.21$, $A_B^a=0.42$, $B_B^r=0.84$, $B_B^a=0.95$ (Zeng et al., 2014) [45].

The repulsive Force from AV [$F_{rep(av)}^{\alpha z}(\vec{r}_{\alpha z})$] is the newly added repulsive force in this study. The anticipated measurable parameters can be the Position of the pedestrian (\vec{r}_α), nearest point-position of the AV circular force-field circumference (\vec{r}_z), the radius of the AV force-field (R_{av}), Repulsive potential $K_{\alpha z}$ is difficult to measure parameter and it can be assumed to be decreased exponentially; hence it can be expressed as $K_{\alpha z}(\|\vec{r}_{\alpha z}\|) = K_{\alpha z}^0 \exp\{-\|\vec{r}_{\alpha z}\|/R_{av}\}$. Since, $\vec{r}_{\alpha z}$, and R_{av} is a measurable parameter; hence, $K_{\alpha z}^0$ needs to be measured. For any fixed object-related obstruction, this potential is estimated to be $10 \text{ m}^2\text{s}^{-2}$ by Helbing and Molnar (1995) [44]. However, this estimation may not be accurate for our case since AV is not a stationary object; however, during the all-red phase in a crosswalk, it may act as a stationary object.

5.4 Simulation Experiments

Simulation is widely adopted to realize pedestrian behavior in a virtual platform (Deb et al., 2017 [52]). In this research work, VADERE (Kleinmeier et al., 2019 [53]) simulation environment is used to simulate the pedestrian behavior using the modified SFM. The steps to conducting a simulation are outlined in Figure 11 and described in the sections below.

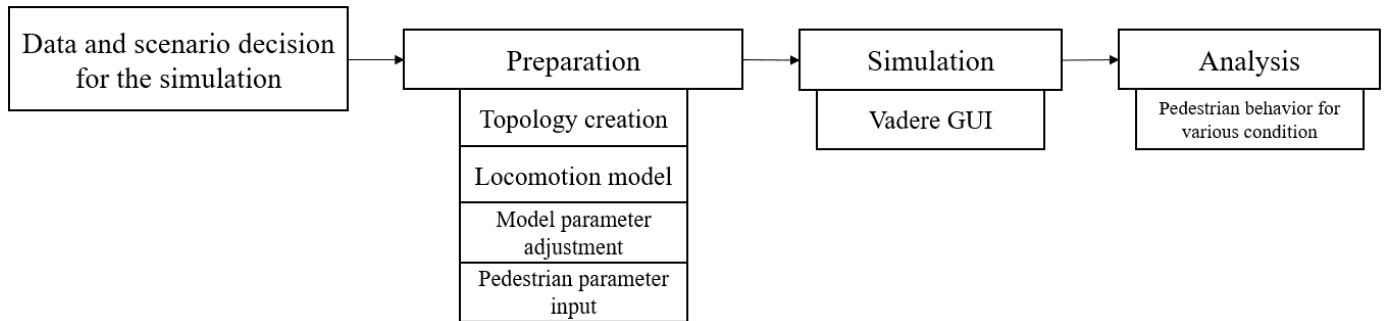


Figure 5-3 Steps of pedestrian dynamics simulation.

After deciding on data and scenarios, the next phase is to develop the simulation environment to experiments. First, it is needed to develop the topology of the crosswalk, and the elements of the crosswalk include pedestrians, a roadway, a pedestrian crossing, and vehicles (AVs). The topology is built in the VADERE software, shown in Figure 10. Every pedestrian needs a start and endpoint. At each edge of the road, there is a starting point of the pedestrians, which is green in color and the end is colored as brown. The obstacles are depicted in grey color. VADERE software includes different locomotion models, where the Social Force Model (SFM) of interest in this study was selected. The parameter in the locomotion model can be programmed in the VADERE interface. For this study, the model parameter is adjusted by changing the repulsion potential for the pedestrian.

5.5 Simulation

The VADERE interface enables the researchers to explore the pedestrian dynamics for various dimensional obstacles, and the degree of repulsion exerted by the obstacles can also be varied. Figure 12 shows a demo depiction of the simulation environment for the pedestrian in a signalized crosswalk. Different parameters are controlled from the VADERE API for simulation purposes, an integral part of the VADERE system. The simulation system can observe the path trajectory of the pedestrian. The blue circle marks the pedestrians, and the corresponding direction of the pedestrians can also be observed by an arrow mark, which is also observed in front of each blue circle. Each simulation session is designed for 100s. Hence, it is assumed that all pedestrians must reach their destination before the 100s.

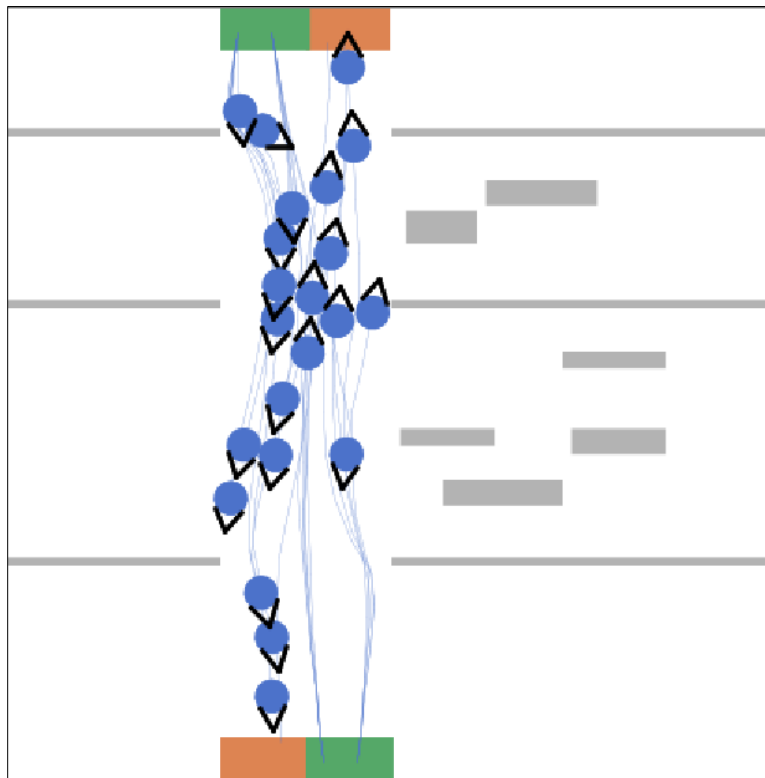


Figure 5-4 Programmable pedestrian dynamics on the VADERE interface.

5.6 Simulation Results and Analysis

We wanted to predict pedestrian behavior in a signalized crosswalk in the simulation platform. Since AVs are still not on the road yet, the degree of repulsion that the pedestrian will feel towards the AVs is unknown, and the repulsion strength is a variable that varies from zero to one. For the familiar objects on the road, cars included, the default repulsive strength of the software is 0.1; hence, we assume that repulsive strength for human-driven vehicles (Figure 12a). In this research, the simulation was performed for different repulsion strengths, including 0.1, 0.2, 0.4, and 0.6, to check the pedestrian behavior for higher degrees of repulsive obstacles like AVs on the road.

For all four scenarios (Figure 13a-13d), the crosswalk has six AV vehicles stopped at the crosswalk. The double-lane road has two vehicles in one lane, and the other has four AV driverless vehicles. The blue-colored lines can observe pedestrian walking trails. Figure 9a-9d shows the four path trajectories of the pedestrians for different repulsive strengths. An undisturbed path trajectory is observed for the pedestrians when the repulsion strength is more minor, like 0.1 or 0.2. However, with the increasing degree of repulsion strength, the path trajectory of the pedestrians becomes chaotic. The AVs' higher degree of repulsion strength forces the pedestrian to cross the crosswalk chaotically.

From the simulation, it is observed that the pedestrian's repulsion strength and chaotic behavior are correlated. It is important to note that pedestrians still cross the road. It shows that the presence of AVs does not fundamentally prevent the regular operation of a signalized crosswalk (i.e., pedestrians still achieve their primary goal of moving from point A to B). However, the chaotic movement of pedestrians can have various implications on traffic operations and travel in general, which is discussed in the following and conclusion section.

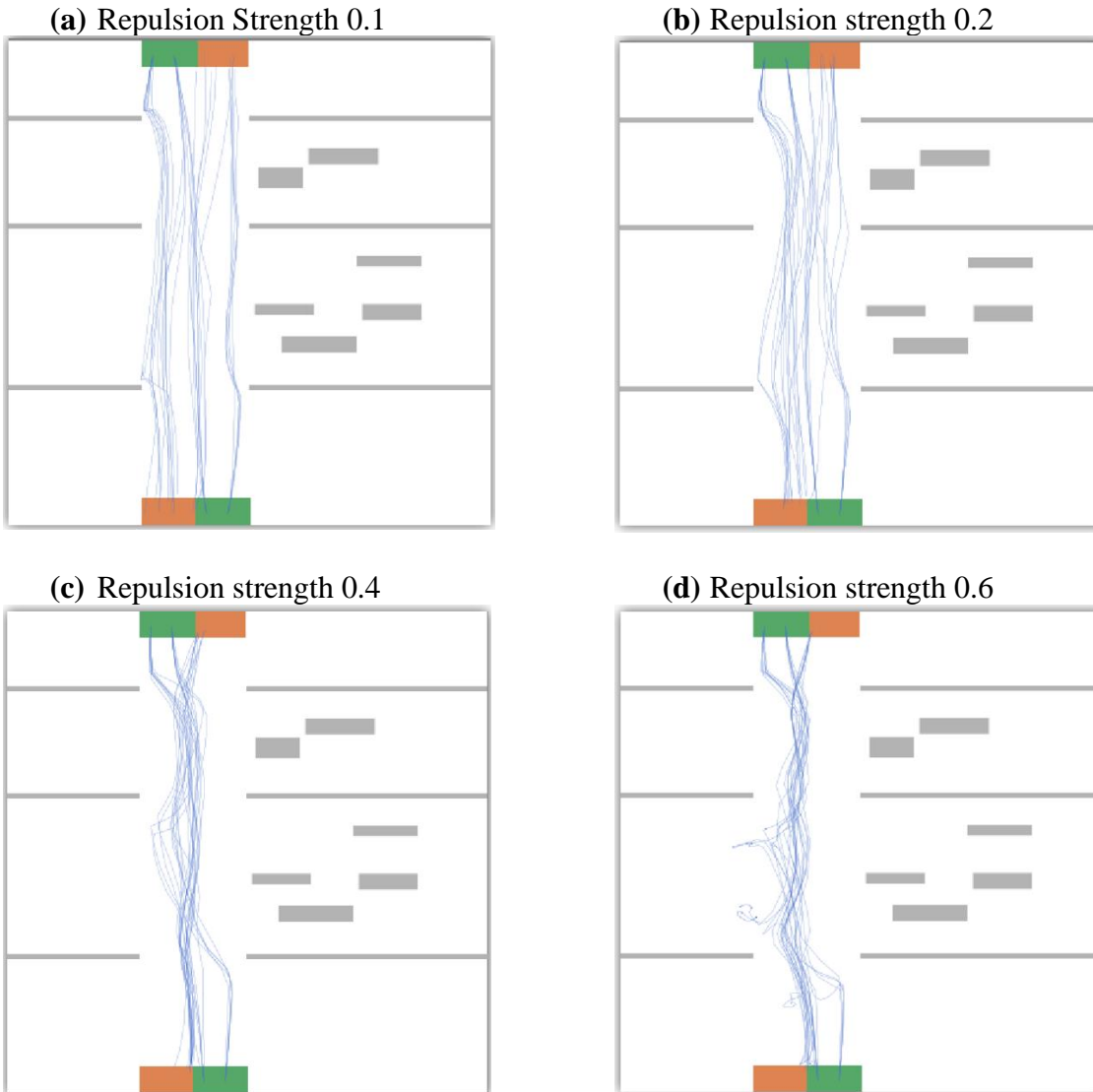


Figure 5-5 Pedestrian dynamics for varying repulsive force on the road.

5.7 Future Study

5.7.1 Comparative Study Between Simulation and VR Study Findings

However, since the pedestrian's behavior towards AVs is unknown to everyone, it is difficult to measure the degree of repulsion only with the simulation result. Therefore, we plan to obtain the pedestrian's walking pattern in a VR (Virtual Reality) environment where the participant will experience autonomous vehicles (AV) and human-driven vehicles (HDV) while crossing the road.

The synthetic VR environment is anticipated to produce a reliable pedestrian walking pattern for AV and HDV. Therefore, the VR lab will provide pedestrian walking patterns recorded during the experiment. Later, we can compare the walking pattern of AV and HDV with the computer simulation model (which provided the degree of repulsion numerically) walking pattern.

Furthermore, since the VR lab provides more realistic results; hence, we can analyze the degree of repulsion that pedestrians will feel on the road by comparing the two results.

5.8 Summary

The proposed modified social force model examines the effects of pedestrian and AV interaction through several scenario-based analyses at a signalized crosswalk. It is anticipated that pedestrians will move chaotically while driverless AVs are on the signalized intersection. The chaotic movement of pedestrians can have various implications on traffic operations and travel. The change in pedestrian behavior indicates that AVs should be trained for chaotic pedestrian movement rather than 'normal' crossing behavior typical in the presence of human-driven vehicles. The chaotic pedestrian movement could imply a longer path for pedestrians to cross than usual, potentially resulting in longer pedestrian crossing times. Longer pedestrian crossing times can impact traffic operations, cause further delays, and potentially require adjustment of signal patterns at signalized crosswalks and intersections. The presence of AV on the road may not impact all the pedestrians at the crosswalk; however, one pedestrian's chaotic crossing behavior will ultimately force the other pedestrian to be crossing the road chaotically. If pedestrians are significantly inconvenienced, they might avoid walking and switch to different travel modes. This will ultimately impact transportation planning on a larger scale. It may require adjustments to traffic operation in a mixed driving situation (i.e., when both AVs and traditional vehicles are on the road).

Chapter 6: Conclusion and Discussion

6.1 Discussion

This project evaluated external human-machine interfaces specifically developed to substitute for the lack of driver feedback and support pedestrians safely, efficiently, and easily interacting with AV. Studies suggest that communication-interface-equipped vehicles are more effective and efficient and seem safer and satisfactory for pedestrians compared to interactions with vehicles without an interface.

Researchers have no consensus on which characteristics constitute an external human-machine interface for effective, efficient, and usable autonomous vehicle-to-pedestrian communication. Some studies have even suggested that, in the future, autonomous vehicles could communicate with other road users via a vehicle-to-infrastructure connection. However, the presented project hoped to show pedestrians' communication and crossing tactics by knowingly considering a broad range of parameters (such as estimation of waiting time and distance gap) or unknowingly (such as the influence of age or gender). At the same time, we can summarize different communication techniques to ease the interaction when needed (in AV) through this study.

This project will exhibit the complexity of the vehicle-pedestrian interaction, in which solely considering some parameters or communication methods may not provide an excellent understanding of the process. This complexity becomes crucial for designing emerging technologies for AV, requiring an accurate comprehension of human road users' behaviors in a traffic interaction to predict their reactions and fulfill their expectations correctly. This study reviewed literature from around the world where pedestrian behavior and the nature of the infrastructure may differ from the United States. This wide-ranging analysis will develop as many appropriate research questions as possible to introduce autonomous vehicles in a different urban environment.

6.2 Problem Encountered during this Project

This project is a dream project for us, the result will not only help us to understand the new traffic, but it will also give us a window to look through the future for pedestrians. And real participant data collection was most challenging because of the covid era. We had to wait a while to get the University IRB approval for the data collection in the VR lab. Now, we are adjusting to the new normal; we hope to finish the work as soon as possible.

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